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Abstract: We analyze changes in the skill content of occupations in US four-digit manufacturing industries between 1999 and 2010. Following a 'task-based' approach, we elaborate a measure of Non-Routine skill intensity that captures the effects of industry exposure to both technology and international trade. The paper adds to previous literature by focusing on both the determinants of demand for Non-Routine skills and their effects on industry productivity and wages. The key finding is that import competition from low-wage countries has been a strong driver of demand for Non-Routine skills during the 2000s. Both technology and trade with low-wage countries are associated with mild cross-industry convergence in skill intensity while trade with high and medium wage countries are at root of persistent heterogeneity across occupational groups. We also find that higher Non-Routine skill intensity has had at best a modest effect on productivity and wages, except for high-skill occupations.

Keywords: Skills, Tasks, Routinization, Trade, Technology.

JEL Classifications: F16, J21, J23, O33

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1. Introduction

This paper elaborates an empirical study of changes in the skill content of occupations in US manufacturing industries over the 2000s. Our goal is to analyze the determinants and the effects of changes in the demand of Non-Routine skills, a particular set of workers' abilities that are used when carrying out analytical and interactive tasks. The relationship between job tasks and skills is a staple of a flourishing strand of research on the relation between capital and labour. The seminal study by Autor, Levy and Murnane (2003) on the effects that computer technology exerted on the composition of employment during the 1990s found a substitution effect for routine-intensive occupations – such as clerks – and complementarity with managerial, professionals and technical occupations. In the face of the argument that the shock wave of the 1990s may have subsided due to stabilization of the computer's life-cycle (see e.g. Vona and Consoli, 2015) we take stock of the empirical evidence and gauge the effect of technology on the demand for skills and on occupational composition in the 2000s. At the same time our analysis takes into account the remarkable growth of international trade due to the expansion of China and other emerging economies (Hanson, 2012). We note that besides very few exceptions (e.g. Lu and Ng, 2013) there are no systematic accounts of how trade has reshaped the skill content of occupations and industries. Filling this gap is the second objective of the paper.

Our analysis yields three main findings. First and foremost, import competition from low-wage countries emerges as a stronger driver of demand for Non-Routine skills than technology in the 2000s. Second, both technology and import from low-wage countries are associated with skill convergence across industries. This is consistent with literature showing that trade-induced adjustments are stronger in industries with lower initial skill levels (Bugamelli et al, 2008; Pierce and Schott, 2012). Furthermore, when allowing for heterogeneity across occupational groups we find that convergence of NR skill intensity across industries is not driven by convergence across occupations. Conversely, heterogeneity across occupational groups is persistent due to imports from high and medium wage countries. The last major finding is that upgrading Non-Routine skills has at best a modest effect on productivity and wages except for high-skill occupations.

The paper is structured as follows. Section two reviews the literature. Section 3 lays out the empirical strategy and Section 4 describes the dataset. The central part of the paper deals with the analysis of the determinants of NR skills: section five presents the baseline model and unpacks heterogeneous effects on different occupational categories. In section six we focus on the effects of NR skills on wages of major occupational groups and productivity. Conclusions summarize and sketch future lines of research.

2. Literature review

The area of innovation studies has made significant contributions to the analysis of the relations between knowledge, industry evolution and competitiveness. This paper focuses on one particular mechanism through which knowledge is applied to economic ends, namely employment. Arguably, besides sporadic bursts of interest (e.g. Nelson and Phelps 1966; Freeman and Perez, 1988; Amendola and Vona, 2012; Consoli et al, 2013; Boschma et al, 2014), the workings of labour markets and the relation between human labour and technology have not been fully integrated in the intellectual apparatus of innovation studies. Yet, employment is the pathway that permits the translation of human know-how into productive activities and understanding what are the mechanisms that shape changes in the employment structure is the key to identify which forms of know-how are relevant at any time as well as the role that technology plays in modifying this know-how.

We explore these issues building on the task-based approach proposed by Autor, Levy and Murnane (2003) (ALM henceforth). In the perspective put forth by ALM skills are ensembles of abilities applied to job tasks. The key intuition is that productive activities can be broken down in functionally different task groups, and that technological change affects the comparative advantage of productive factors, i.e. workers, machines, in performing a certain task (Levy and Murnarne, 2004). This approach opens up new possibilities for understanding the process by which individual abilities emerge, combine, or are selected out as a result of innovation and structural change and is an appealing conceptual framework to address issues that are central for innovation studies. To begin with, it allows for a more flexible interpretation of the relation between labor and capital in performing work tasks, and this is especially relevant in those contexts in which technology plays a dual role, partly complementing and partly substituting human work. Clearly this approach is grounded in an interdisciplinary view whose central tenet, traceable to Herbert Simon (see e.g. 1969), holds that machines perform better physical and cognitive 'routine' tasks that can be codified in the form of instructions while humans retain a cognitive comparative advantage at 'Non-Routine' activities that involve problem-solving, pattern recognition (e.g. Langlois, 2003) and personal interaction like, for example, communicating with others (interpersonal skills) or interpreting information (analytical skills). Yet another advantage of the task approach is that it accommodates empirical findings of non-neutral labor market outcomes due to the diffusion of new General Purpose Technologies (GPTs)[1] and associated changes in the organization of production for which the traditional capital-skill complementarity hypothesis (i.e. Krusell et al. 2000) does not suffice.[2]

[1] Note that the task-based model suits also other radical technological transitions, for example electrification in the IXX century (Gray, 2013).

[2] Within the economics literature on the effect of ICT technologies on the labor markets, early studies generally explain the increase in the skill premium using a demand-supply framework augmented for directed technical change (see, e.g., Krueger et al., 1993, Katz and Murphy, 1992; Autor et al, 1998; Goldin and Katz, 1998; Acemoglu, 1998). This approach, however, is unable to explain polarization and has hence been replaced by the more general routinization hypothesis discussed in the main text (see Autor, Katz and Kerney, 2008). The debate is well summarized in Acemoglu and Autor (2011).

Building on the above, we propose an analysis of the determinants and effects of changes in the demand of Non-Routine (NR henceforth) skills in US manufacturing industries during the period 1999-2010. This time window is especially interesting due to the co-occurrence of key global events such as China's admission to the WTO and the great recession after 2007.

Previous studies on the determinants of change in the demand for skills draw attention to ICTs and trade. ALM (2003) first put forth the proposition that ICTs induced 'polarization' in employment and demand for skills, that is, decline of routine-intensive jobs and wages relative to occupations that are either at the top or at the bottom of the earning distribution (Autor et al, 2008; Goos and Manning, 2007). This is because, as discussed before, computer capital substitutes for routine tasks, thus reducing the demand for routine-intensive occupations, while increasing the productivity of Non-Routine analytical and interactive skills and, thus, the demand for high skill professionals. Interestingly, these empirical regularities have been observed also in a large panel of economies, not just in the US.[3] Recent evidence also suggests that the influence of ICTs has waned away during the last decade. Weber and Kauffman (2011) for example note that ICT-related investments in US manufacturing reached a plateau during the 2000s, and that the lion share of capital spending is now on maintenance activities rather than new technology acquisition. Also Aizcorbe et al (2006) call attention to a break in the technological trajectory of ICTs sometime in the early 2000s that is ascribed to a combination of changes in economies of scale and a shift in product mix.[4] This, while not necessarily implying reduced importance of technology, calls at least for a reconsideration of the one-to-one mapping between ICTs and NR skills. After all it seems plausible that, after take-off and growth, the trajectory of ICTs may have reached a

[3] See Spitz-Oener (2006); Goos et al (2009); Acemoglu and Autor (2011); Jaimovich and Siu (2012).

[4] See also Oliner and Sichel (2000), Wolff (2003) and Basu and Fernald (2007). To illustrate, the product cycle for semiconductors (i.e. the lag between successive releases) shifted back to a 3-year period since 2000 (Jorgenson et al, 2008) after being reduced to 2 years during the intense competition of the mid-1990s. Recent examples of ICTs diversification also confirm this e.g. Hubbard (2003) and Athey and Stern (2002).

stage of maturity and, as codification has caught up with the skills that pushed the technological frontier in the 1990s (Vona and Consoli, 2015), the dynamics of both productivity and wages have adapted accordingly. The first goal of the paper is to take stock of existing evidence and assess whether technology continued to be during the 2000s a major driver of the demand for skills, and in particular if it has spurred any further divergence across occupations and industries.

The debate on the changes in the skill content of the workforce has been recently enriched by the inclusion of trade as key explanatory factor. This is not surprising considering the remarkable pace of expansion of China and of various emerging economies that have transformed the global import-export matrix (Hanson, 2012). With regards to the US, the general agreement is that higher exposure to foreign competition had a negative employment effect, especially after China's entry in the WTO in 2001 (Pierce and Schott, 2012; Autor et al, 2013). The literature draws attention to two mechanisms. On the one hand greater fragmentation of supply chains (Baldwin, 2011) has opened up the scope for offshoring of routine tasks involving minimal complexity (Blinder, 2009). On the other hand domestic producers have reacted to foreign competition by switching to higher quality products and innovations requiring intensive use of Non-Routine tasks (Verhoogen, 2008). In general much empirical evidence lends support to the conjecture that the impact of trade has been heterogeneous across industries and occupations.[5] With the notable exception of Lu and Ng (2013), however, few have analysed the impact of trade on the skill content of US industries during the large uptake of trade with low-wage and emerging countries. Addressing this issue is the second objective of this paper.

[5] Note that large trade shocks are not limited to the US: empirical evidence shows a direct effect of trade shocks on returns to skills in both developing (Verhoogen, 2008; Amiti and Davis, 2012) and developed countries (Guadalupe, 2007; Raitano and Vona, 2013). Bugamelli et al. (2008) find that the Euro and increased competition from China induced restructuring in the workforce composition, especially among low-tech sectors.

By tackling the two questions outlined above, this study adds to previous literature in three ways. First, it focuses both on the determinants of the demand for NR skills and the effects of NR skills on performance, captured through changes in industry wages and productivity. Second studies on the determinants of NR skills (Autor et al, 2003; Lu and Ng, 2013) arguably neglect the dynamic process by which the composition of the workforce gradually adapts to a new, ex-ante undetermined, target-level of NR skills. Our empirical strategy accounts for this by means of standard system-GMM techniques. Third, unlike past work our dependent variable is not the employment share of occupations ranked according to initial skill levels (see Autor et al. 2013) but, rather, a measure that combines in an unconstrained way both industry-level changes in NR skills *within* occupation and in the employment shares *between* occupations. We believe that this is an appropriate choice considering that technological revolutions induce composition effects on employment shares of occupations as well as changes in the skill content (Autor et al, 2003; Vona and Consoli, 2015).

3. Empirical Strategy

Let us now illustrate our empirical strategy. To fix ideas, we are primarily interested in explaining Non-Routine skill intensity at time *t* in industry *i* (NRI_{it}) as a linear function of trade and technology variables. In the second part of the paper we focus on an indicator of performance Y as function of NR intensity, trade and technology proxies. In formulae:

$$NRI_{it} = f(trade_{it}, tec_{it})$$

$$Y_{it} = f(trade_{it}, tec_{it}, NRI_{it})$$

The assumption of linearity of *f(.)* is not just for the sake of simplicity. This paper is mainly an empirical exercise and relies on previous work to derive testable predictions, so we do not put forth theoretical justifications in support of including interactions or nonlinear effects. In addition, relevant literature keeps the empirical specification to a minimum in order to avoid misinterpretation of the effects of interest. Accordingly, we opt for a parsimonious specification. In the studies by Autor et al (2003) and Lu and Ng (2013) the identification of the effects of interest is warranted by the inclusion of unobservable individual effects and/or by the use of IV. An IV approach would be appealing for us because unobservable time-varying factors likely affect both the demand for NR skills and the evolution of technology. However, previous works have been unsuccessful in finding appropriate instruments both for trade and technology proxies. For example, Autor and Dorn (2013) and Autor, Dorn and Hanson (2013) use NR skill levels in the 1950s as instrument for NR skill levels to explain changes in employment shares across occupational groups in later decades. This is done under the caveat that instruments based on initial conditions are suitable for explaining the demand for NR skills in the 1960s but lose explanatory power for the following decades, thus becoming weak predictors for the crucial decade of the ICT revolution.

Another important source of bias is true state dependence in the data generating process. In our case the 0.97 point estimate of the autocorrelation coefficient for NR skills indicates that state dependence characterizes the adjustment in industry demand of NR skills.[6] Such a high degree of persistence is not surprising considering that both the demand and the supply of skills are variables that change slowly over time. For what concerns demand, this is due to non-negligible hiring and firing costs due to skill specificity, while in the case of supply there are significant lags in the adjustment through training and education. Note that in past work, e.g. ALM (2003), state dependency may have been less severe because the time-unit was a decade or a 5-year period. More recently Lu and Ng (2013) used an industry-by-year panel and correctly conclude that their findings do not change when dynamics is properly accounted for. However their point estimates of the effect of the lagged dependent variable

[6] Similar results emerge when using standard tests for serial correlation and presence of unit roots.

range between 0.05 and 0.15, well-below that of our data.[7] A similar argument applies to our measures of performance, i.e. industry wages and productivity, which also exhibit high persistency with estimated autocorrelation coefficients above 0.9. Following on these remarks, our specifications in eq. 1-2 become:

$$NRI_{i,t} = \rho NRI_{i,t-1} + \beta_1 tec_{i,t-1} + \beta_2 trade_{i,t-3} + \mu_i + \mu_t + \varepsilon_{i,t} \qquad (1)$$

$$Y_{i,t-1} = \rho Y_{i,t-1} + \alpha_1 NRI_{i,t-1} + \alpha_2 tec_{i,t-1} + \alpha_3 trade_{i,t-3} + \mu_i + \mu_t + \varepsilon_{i,t}, \qquad (2)$$

where μ_i, μ_t and $\varepsilon_{i,t}$ are respectively a industry effect, a time effect and a generic disturbance term, independent across individuals. While it is well-known that under these circumstances OLS and Fixed Effect estimators deliver biased estimates the effects of interest (Nickell, 1981), the debate as on what is the best fix is still open. The system-GMM estimator (Arellano and Bover, 1995; Blundell and Bond, 1998) has gained some consensus among applied economists. The basic rationale underpinning these estimators is that of instrumenting the lagged dependent variable with its lags or lagged differences. Within this class of estimators, the system-GMM reduces the small-sample bias of the differenced-GMM (Arellano and Bond, 1991) when the endogenous variables are persistent using moment conditions both for the equation in level and in first-differences (Bond, 2002). Such a bias is due to the fact that the pure random disturbance generated when differencing a persistent variable is by definition a weak instrument.

The inclusion of the lagged dependent variables does not fully address the issue of endogeneity of trade and technology variables, even if the lagged dependent variable is a good proxy for industry-time-varying factors that are likely to bias our effects of interest. For what concerns technology, we exploit the long data series available for our technology proxy

[7] High persistence is observed also even when using the measures of NR skills of Lu and Ng (2013). The latter study uses differenced GMM (Arellano and Bond, 1991) instead of the more general system GMM (Blundell and Bond 1998) which, we argue, may generate a downward bias of the autocorrelation coefficient. Using a Montecarlo experiment Hauk and Wacziarg (2009) show that the differenced GMM tends to considerably underestimate the autocorrelation coefficient as compared with a system GMM estimator.

and use past values as proxies of current ones. For what concerns trade variables, we could have followed the same route but we would lost two years for our analysis since trade variables are available until 2007 only. We therefore opted for including trade variables with a 3-year lag rather than instrumenting them also to avoid he problem of having 'too many instruments' compared to the number of observations (Roodman 2009a). Likewise since available data for technology are only available until 2009, we lag our technology proxy. This peculiar lag structure is the best option for preserving an acceptable time span in the analysis of the 2000s, and for ensuring the inclusion of the recent economic recession.[8]

Further details of the empirical strategy are outlined in the section on the results. Let us now move to illustrate the dataset and the construction of the variables.

4. Data and variables

Our empirical analysis combines data from three different sources. We use U.S. Bureau of Labor Services (BLS) data for employment and hourly wages across industries (four-digit occupations based on the Standard Occupational Classification System – SOC henceforth) and four-digit NAICS. The latter is matched with information on occupation-specific task content, the O-NET abilities survey of the US Department of Labor. Lastly, we use NBER data for variables on International Trade Data, technology, productivity and remaining controls. Data construction and measurement are detailed below, while further details are provided in Appendix B.

Construction of task variables

The US Department of Labor's O-NET abilities survey is the main source of information to compute our task variables. This database gathers information of worker attributes and job

[8] Interestingly, the financial crisis of 2007 has no significant effect on our variables of interest. The same holds when we include proxies for industry demand. Our results are also robust to changes in the lag structure (not surprising since our explanatory variables are also highly persistent).

characteristics from questionnaires aimed at both job incumbents and occupational analysts (see Tippins and Hilton, 2010). To keep up with changes in the US labor market O-NET data are regularly updated and adapted in a way that entails two sources of variation for the task content: (i) occupations are added, reclassified or eliminated in accordance with periodical revisions of the SOC structure; (ii) scores of worker characteristics increase or decrease as a result of changed importance. We kept track of all revisions over the period 2002-2010 and created a unique dataset of 855 four-digit SOC occupations. O-NET information on job content has been matched with industry-occupation total employment from BLS for the period 1999-2010.[9] Since the first usable wave of O-NET is of 2002 we lack information on employee abilities in the period 1999-2001. To cope with this, we assign time invariant from the 2002 wave of O-NET to observations that belong to the period 1999-2001. Using crosswalks across different datasets, we obtain a balanced industry-by-year panel dataset including 86 manufacturing industries for the period 1999-2010.

The key dimensions for our variables of interest are job-specific characteristics such as e.g. communicating with others (NR Interactive), interpreting meaning of information (NR Cognitive), performing administrative activities (Routine Cognitive), performing physical activities (Routine Manual) – further details in Appendix B3. Accordingly, the scores assigned from the survey's respondents generate vectors of basic tasks that are specific to each SOC occupation. While such basic tasks are common to most jobs, a particular combination of scores in the use of each task distinguishes occupations from one another.

Our task constructs are built from a detailed examination of O-NET Work Activities and Work Context, i.e. the scores in basic tasks. These items are subsequently grouped together in four main macro-categories: Non-Routine Cognitive (NRC), Non-Routine Interactive (NRI),

[9] BLS data on employment for the period 1999-2010 are built on different industry classification schemes: the 1987 Standard Industrial Classification (SIC1987) until 2001, the 2002 North American Industry Classification System (NAICS) until 2006, the 2007 North American Industry Classification System (NAICS) currently in use. We developed concordance tables details of which are in Section B1 of the appendix.

Routine Cognitive (RC) and Routine Manual (RM). Table B1 in the appendix lists the 40 O-NET task items used in this study, ten for each category. The macro categories are computed by summing the score of importance for a particular SOC occupation. The index of task intensity is as follows:

$$NR\ Intensity_{it} = \sum\nolimits_j Emp\ Share_{ijt} * \left[\frac{NRC + NRI}{RM + RC}\right]_{ijt},$$

where NRC, NRI, RM and RC are the task constructs outlined above for industry *i* and occupation *j* in year *t*. $Emp\ Share_{ijt}$ refers to employment share in industry *i* and occupation *j* in year *t*, constructed using data at the four-digit NAICS and four-digit SOC from BLS. To define skill categories we build on the classification of Acemoglu and Autor (2011) by including additional items (see Table B1 in the Appendix).[10] The strategy of expanding the skill set is coherent with the framework outlined before and, in particular, with the idea that the evolution of ICTs triggers complementarities with forms of know-how that were not foreseeable at the inception of the technological revolution (Vona and Consoli, 2015). Moreover, we partially depart from previous literature as our chosen measure is not the employment share of occupations ranked according to initial levels of Non-Routine skill content (see Autor et al. 2013) but, rather, an industry-level measure of Non-Routine skills. We believe that this construct captures both changes in the employment shares *between* occupations and changes in Non-Routine skills *within* occupation. This feature distinguishes the present paper from previous work based solely on within variation in task constructs due to changes in the composition of employment (e.g. Autor et al., 2003; Autor et al., 2013).[11]

[10] Compared to the Non-Routine Cognitive set of Acemoglu and Autor (2011) we add the following items: Judging the Qualities of Things, Services, or People; Evaluating Information to Determine Compliance with Standards; Making Decisions and Solving Problems; Updating and Using Relevant Knowledge; Organizing, Planning, and Prioritizing Work; Coordinating the Work and Activities of Others and Developing and Building Teams (cfr. Table B1 in the Appendix).

[11] We carried out several robustness checks with different measures of task content at industry level. Results are robust to the different definitions of our task variable. See Appendix B for further details.

Furthermore, to capture heterogeneity in the effect of our variables of interest across occupations we follow Autor and Dorn (2013) and differentiate between three broad occupational groups. The first category including occupations that are intensive in Non-Routine tasks (NRI and NRC) is labeled as high skill (HS henceforth) group. The second category encompasses routine-task intensive activities and contains medium skill occupations (MS henceforth). The last group features low-skill jobs and contains low skill occupations (LS henceforth). Similar to what was done for the task measure above, we build three different task measures referring to the three broad occupational categories: high skill (*NR intensity HS*), medium skill (*NR intensity MS*) and low skill (*NR intensity LS*).[12]

Labor Productivity and Hourly Wage measures

We analyze the effects of changes in Non-Routine tasks by focusing on labor productivity and hourly wages. The former is an aggregate (industry-level) measure of performance while the latter varies across occupations and thus provides useful insights on the impact of our variable of interest, NR intensity, over different types of workers. Labor productivity ($Prod_{it}$) is computed as value added per worker at the four-digit NAICS. This is the total value added in $ million per 1000 employees and is available on a yearly basis for the period 1989-2009. Information on total value added and employment is extracted from the NBER-CES manufacturing industry database (Becker and Gray, 2013). The source of the other performance indicator, average hourly wage for four-digit occupations, is BLS. Following the same logic underlying the construction of the task measures, we seek to capture heterogeneity across the three occupational categories by considering group-specific hourly wages, namely *Wage HS*, *Wage MS* and *Wage LS*. [13]

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[12] All task measures are aggregated at the occupational group by weighting for employment shares of each occupation belonging to the group.

[13] The aggregate hourly wage at the occupational group level is weighed by employment shares.

Measures of technology and trade

We proxy investments in ICTs by using information on investment in capital equipment per worker available from the NBER-CES Manufacturing Industry database (Becker and Gray, 2013). This simple measure is appropriate for our purposes considering the vast literature on the pervasiveness of automated processes in production technology (e.g. David and Wright, 2003; Brynjolfsson and McAfee, 2011) and their capacity to capture embodied technical change (Cummins and Violante, 2002).

We measure exposure to trade through an index of import penetration that are widely used in the literature (Bernard et al., 2006; Lu and Ng, 2013). Import penetration ratios are a reliable measure of the evolution in exposure of manufacturing industries to foreign competition. Accordingly, we define two measures of import penetration. *Imp Pen Hi-Med*$_{it}$ is the ratio of the total value of US imports from high and medium wage countries over the total value of shipments and imports minus exports. To capture effects coming from low-wage countries, we also define import penetration from low wage countries (*Imp Pen Low)* [14] and for China (*Imp Pen China*). To construct our measures, we employ U.S. import and export data of the manufacturing industries for the period 1996-2007 compiled by Peter Schott, and data on value of shipments from the NBER-CES manufacturing industry database.

Figure 1 shows the prolonged contraction in US manufacturing employment with two sharp accelerations coinciding with the recessionary phases of 1999-2003 and 2007-2010. Note that on both occasions the contraction has been relatively stronger for Medium- and Low-Skill occupations relative to High-Skill occupations.

[FIGURE ONE ABOUT HERE]

[14] Low-wage countries are those with a GDP per capita less than 5% of US per GDP per capita.

Table 1 presents basic statistics with details on the reference period and the data source. Figure 2 offers preliminary insights into the relation between the relative demand for skilled labor and our main explanatory variables, namely capital equipment and import penetration, over time. We observe that import penetration from low wage countries accelerates faster than import from high- and middle-income countries especially after 2001[cf. quadrant (b) and (c)]. Incidentally, this pattern is very much driven by trade with China [quadrant (d)].

Figure 3 shows the smoothed change of NR skill intensity across all sectors ordered by initial NR intensity in the period under analysis. The decreasing shape shows that skill growth was faster for industries with lower initial NR intensity, thus providing a first insight into cross-industry convergence.

[FIGURE 2 ABOUT HERE

[FIGURE 3 ABOUT HERE]

[Table 1 ABOUT HERE]

Let us now turn to the analysis of the determinants and the effects of changes in the demand for Non-Routine skills.

5. Determinants of Non-Routine Skills

This section presents the analysis for the demand of NR skills at industry level. Table 2 shows the baseline results. These are extended in Table 3 by allowing for heterogeneity across different occupational groups. To ease the interpretation, recall that our measure of NR skills is basically tantamount to a general measure of quality of employment.

Baseline specification

Table 2 shows a series of specifications progressively enriched by various controls. The common covariates are the lagged dependent variable, lagged capital equipment, our chosen proxy for ICTs, *Cap Equip*, and two time-invariant dummies for low- and medium-tech industries (*Low Tech* and *Med Tech* respectively).[15] Both lagged capital equipment and the lagged dependent variable are instrumented: the former with the second lag, the latter with lags from 2 to 5. Four preliminary observations are in order. First, standard tests validate our specification: the Hansen test does not reject the null hypothesis of instruments' exogeneity and the Arellano-Bond tests always fails to reject the alternative hypothesis of second-order autocorrelation.[16] The validity of the standard specification tests applies to all the models presented in the remainder of the paper. Second, dynamic specification reduces the bias of the estimated effects, especially for capital equipment. This is evident from a comparison between Table Table **2** and Table A1 in the appendix where the main specifications (Model 1 and 3) are estimated using OLS and FE without the lagged dependent variable. Third, the effects of the lagged dependent variable $\hat{\rho}$ (well above 0.9) and of the two dummies *Med Tech* and *Low Tech* (negative relative to the reference category *High Tech*) point to high persistence in the process of adaptation in NR skill intensity. Model 1 uses only *Cap Equip* as external explanatory variable. This is akin to the specification of the classic ALM (2003) paper, with the exception of the lagged dependent variable. The point estimate is positive but not statistically different from zero (p-value=0.348) to indicate that the aggregate effect of ICTs adoption on Non-Routine skills weakened over the last decade. The specification of Model 2 includes trade with high- and medium-wage countries and is equivalent to the model used by Lu and Ng (2013) augmented with the lagged dependent variable. Our results corroborate their finding of a positive and significant effect of import penetration on the skill quality of the workforce over the period 1999-2010. In Model 3, our favorite specification,

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[15] To control for the technological content of different industry aggregations we use three dummies for low (*Low Tech*), medium (*Med Tech*) and high (*High Tech*) technology sectors in manufacturing (according to the Eurostat classification). For further details, see Table B3 in the Appendix.

[16]The differenced Sargan test (not shown here) generally confirms that system GMM is the appropriate specification compared to differenced GMM.

the effect of trade is decomposed by considering import penetration from low wage countries. Unlike Lu and Ng (2013) we find that the positive and significant effect of trade with high- and medium-wage countries is totally absorbed by *Imp Pen Low*. [17]

The inclusion of *Imp Pen Low* yields a twofold increase of the coefficient of capital equipment, which is now statistically significant at 95% level. Although the correlation between *Imp Pen Low* and *Cap Equip* is rather modest -0.17, it is likely that industries with higher exposure to trade from low-wage countries adjust not only their labor force skills but, also, the use of complementary inputs like capital equipment. Model 3a and 3b deal with this issue by re-estimating Model 3 split respectively for industries below and above the pre-sample median of the initial level of *Imp Pen Low*, computed for 1989-1995. The results are striking: while the point estimate of *Imp Pen Low* (resp. *Cap Equip*) is statistically significant (resp. insignificant) only in industries with highly exposed to competition of developing countries, the opposite holds for *Cap Equip* (resp. *Imp Pen Low*). Interestingly, the coefficient of *Cap Equip* is much higher in industries with high exposure to *Imp Pen Low*, but displays a high variability that makes it statistically insignificant. This is broadly consistent with the finding of Autor, Dorn and Hanson (2013) that the effects of trade from low wage countries and of technology do not overlap. From this we conclude that differences in the effect of technology across industries may not be visible unless import from low wage countries is accounted for.

The statistical significance of the estimated effects may not correspond to economic significance. This is not the case here since the size of the two short-run effects of *Cap Equip* and *Imp Pen Low* reflects the increasing importance of the latter relative to the former. In particular, a one standard deviation increase in *Cap Equip* (resp. *Imp Pen Low*) explains 2.1%

[17] Table A2 in the Appendix shows that the main results of Model 3 are confirmed using the between estimator suggested by Hauk and Wacziarg (2009), which is more robust to measurement errors than the system GMM.

(resp. 3.6%) of a standard deviation in *NR intensity*.[18] Note that the long-term effects of these two variables are considerably larger, i.e. more than 11 times, than short-term effects.[19]

[Table 2 ABOUT HERE]

The descriptive analysis in Figure 3 may suggest a mild tendency towards industry catching-up in the level of NR skills. However, high values of the autocorrelation coefficient for NR intensity together with negative and statistically significant coefficients of the dummies *Low Tech* and *Med Tech* in Table 2 point to considerable persistence in the demand for NR skills. We investigate this by splitting the sample using the median of the initial level of NR skill intensity and excluding the *Low Tech* and *Med Tech* dummies. Models 3c and 3d illustrate that *Imp Pen Low* and *Cap Equip* have a large and statistically significant effect only in industries with a below-median initial skill level. In turn, the positive and near significant (p-value=0.138) effect of *Imp Pen Hi-Med* in skilled industries is offset by a negative and significant effect in unskilled industries. In sum, at industry level, trade from low-wage countries and technology emerge as the strongest convergence force for NR skills, while trade with high wage countries is a mild source of divergence.

In sum, two major findings stand out so far. First, *Imp Pen Low* induces restructuring and skill adaptation especially in low-skill industries that are arguably more exposed to competition from low wage countries. The fact that the adjustment to foreign competition depends on the initial skill level and is a source of skill convergence across industries is in line with previous studies on both European countries (Bugamelli et al, 2008) and the US (Pierce and Schott, 2012). Second, technology, proxied by capital equipment, is not a source

[18] A possible objection is that the effect of *Imp Pen Low* is reduced by the particular lag structure chosen (see section 2). To check for this, we replicate the analysis using a shorter lag structure and find that both the size and the statistical significance of the estimated coefficients is fully consistent with those of Model 3. Results are available upon request.

[19] The long-run effect is equal to the short run effect multiplied by $1/(1-\rho)$ where ρ is the estimated auto-correlation coefficient.

of skill divergence but, rather, of mild cross-industry convergence. This suggests that as ICTs have matured and activities to them associated have been codified, the impact of technology may have faded away (Vona and Consoli, 2015).

Heterogeneity in occupational skill content

Models 1-3 in Table 3 replicate the analysis of Table 2 by allowing for heterogeneity across the three occupational categories defined earlier. As expected from employment patterns depicted in Figure 1, the results reveal substantial heterogeneity across occupational groups. First, skill persistence, captured by the lagged NR occupation specific coefficient is stronger for supervised occupations, viz. LS- and MS-, relative to HS occupations. With regards to our main explanatory variables, *Imp Pen Hi-Med* has a negative and significant effect on LS but a positive effect on the other occupations. Taking into account significance levels, and considering the results for above-median split sample of Table 2, we conclude that *Imp Pen Hi-Med* is a source of skill divergence mainly between middle and low occupations. Second, in accord with ALM (2003), *Cap Equip* continues to exert a polarizing effect since skill upgrading is stronger for high and low occupations compared to middle occupations. Third, *Imp Pen Low* is also a source of significant skill polarization. This result, in line with the Heckscher-Ohlin model, suggests that trade is a source of inequality in the use of certain inputs or tasks, in this case Non-Routine tasks, especially between countries with very large differences in endowments. For what concerns low skills the net effect depends on the direction of the adjustments that follow trade-induced job loss.[20] On the whole, the share of low-skilled occupations will be lower but the surviving workers will be more qualified.

[20] For the sake of space, we do not report results for employment which are consistent with the literature. In particular, *Imp Pen Low* has a negative, large and significant effect on employment of low-skill workers. A recent study by Autor, Dorn, Hanson and Song (2013) finds that workers initially employed in industries with higher exposure to Chinese competition are more likely to change job and to move out of manufacturing altogether, high-wage workers are able to relocate before large-scale restructuring occur and, thus, to avoid significant earning losses, while low-wage workers, generally less mobile, are more likely to either be laid off.

[Table 3 ABOUT HERE]

Models 4-6 in Table 3 further articulate the effect of trade by breaking down *Imp Pen Low* into two import penetration ratios, thus isolating imports from China (*Imp Pen China*) from those of other low-income countries (*Imp Pen Low No China*). *Imp Pen China* has a positive effect on all groups, especially the high-skilled for which the effect is also statistically significant. The coefficient for the HS category is in line with earlier remarks on the fragmentation of production chains (Baldwin, 2011) and the comparative advantage that countries like China have gained in labor-intensive sub-activities within high-tech industries (Krugman, 2008; Hanson, 2012). In particular, the demand of NR skills is expected to increase especially among HS occupations as a result of jobs intensive in routine tasks being offshored to low-wage countries. The positive effect of *Imp Pen Low* on the NR skills among lower occupations is fully captured by the effect of other low-wage countries except China. This finding is consistent with recent evidence on the shift from low- to middle skill-production in China (Amiti and Freund, 2010). By analogy, the selection effect on the quality of the workforce in low-skill occupations should be stronger for low-wage countries that remain specialized in low-skill production.

Note that the results are qualitatively confirmed by the use of the BE estimator (see Table A2 in Appendix A). These findings also suggest a substantially heterogeneous effect of trade and technology across occupational groups which is further corroborated by the graphical analysis on the differences between the estimated coefficients (see Figure A1 and A2 in the Appendix).

6. Effects of NR skills

This section presents the analysis of the effects of NR skills in terms of performance at industry level divided in two parts. The first focuses on productivity, the second on wages.

Productivity

Table 4 shows results for the analysis of productivity growth measured as value added per worker. To take into account the dynamic nature of the process, our estimations are based on system GMM.[21] In particular we use a catching-up equation (e.g. Griffith et al, 2004) in which the dynamic term is the lagged distance-to-frontier effect computed as the difference between the productivity of each industry and that of the most productive industry divided by the productivity of the latter (*Distance to frontier*).[22] The inclusion of the distance-to-frontier term allows modeling productivity dynamics as dependent on the scope of catching up of the specific industry at stake (Nicoletti and Scarpetta, 2003). All variables are in log to allow direct interpretation of the effects in terms of elasticity.

Table 4 ABOUT HERE

The first specification, Model 1, shows that the effect of skill upgrading is, as expected, positive and statistically significant. In particular, a 1% increase in the intensity of *NR intensity* yields a 0.18% increase in productivity. Note that this is akin to a short-term effect since it is obtained by controlling for distance-to-frontier term. The coefficient for distance-to-the-frontier suggests cross-industry convergence with a large effect of 6.8% catching-up on a yearly basis. Our catching-up specification of productivity dynamics captures faster productivity growth in industries with lower initial level, as the positive sign of the dummies for middle- and low-tech industries confirms. However, this specification suffers from an omitted variable bias as many other sources of productivity growth are not included. We address this shortcoming by including various proxies for skills and other drivers of productivity.

[21] As in the case of skills above, standard statistical tests corroborate the validity of our choice.

[22] We use information from our productivity measure and define the productivity distance in sector *i* and year *t* as the value of the most productive industry in year *t*: $Max(Prod)_t$

The addition of industry employment shares of HS and MS, using LS as ‘reference group’, to Model 2 reverses the result for *NR intensity*, which is now negative. In turn, higher shares of HS and MS workers are observed to have positive productivity effects with short-term elasticity respectively of 0.15% and 0.1%. This suggests that the relative quantity of high-skilled workers matters more than the relative quality of the workforce for industry productivity growth.

To shed further light on the catching up the sample is split in two groups according to initial productivity levels, respectively above (Model 2a) and below (Model 2b) median productivity of the pre-sample period 1990-1998. Observe that catching-up is concentrated in industries above median productivity level. Since the distribution of value added per capita is right-skewed, industries with average productivity level catch up with those at the frontier. The next step consists in including other productivity-drivers selected on the basis of previous studies. The specification in Model 3 includes *Cap Equip* and the usual proxies of international competition. Both sets of variables are expected to positively affect productivity growth. The former effect derives straightforwardly from any endogenous growth models while the latter depends on firm selection in new trade models à la Melitz (2003). We observe that, first, the effect of *NR intensity* is again negative and near significant (p-value=0.130) while the elasticities associated with *Emp Sh HS* and *Emp Sh MS* increase above 0.2. Secondly, the coefficient *Cap Equip* is, as expected, positive and statistically significant with a modest short-term elasticity of 0.01. Third, the two measures of import penetration have no particular influence on productivity. But, if any, the influence of trade tends to be negative.

Comparing these results with existing literature, for what concerns technology they resonate with evidence on the positive impact of ICTs on industry productivity (Siegel and Griliches, 1992; Jorgenson et al, 2008). For what concerns trade, the effect is not in line with new trade models à la Melitz (2003), and it is important to remark that this last set of results are not always robust to the use of a robust BE estimator (see Appendix). Finally, the finding on the effect of NR skills is consistent the study by Wolff (2003) showing that growth in cognitive skills has a positive, albeit modest, association with industry productivity growth. Reassuringly, this main result on the effect of NR skills on productivity is robust to changes in specification and to different productivity measures.[23]

Industry Wages

Change in wages is frequently used in the study of the dynamics of skills and employment. The existing literature analyzes extensively on the effect of routinization and trade on wage inequality, i.e. the wage difference between higher and lower occupations. The usual assumption is to rank occupations according to their initial skill levels, so that the effect of interest is not skill upgrading on wages but rather trade and technology on wage mediated by the initial skill level. In this section we address a complementary research question: how much do wages react to upgrading in the NR skill content of an occupation? Wages are interpreted here as a measure of economic performance at occupational level.[24] This shift in perspective is possible since our dataset allows building skill measures for occupational macro-groups that vary over-time and across industries.[25] All else equal we expect that workers with higher *NR intensity* be paid more. .

The evolution of wages of occupation *i* in industry *j* is characterized by true state dependency which leads us to adopt, for the same reasons discussed earlier with regards to *NR intensity*, a dynamic specification. On the other hand, however, the lagged dependent variable is not normally included in the standard Mincerian wage equation. Hence, in Table 5 we compare

[23] In particular, it is robust to a classic dynamic specification rather than to a catching-up specification, a BE estimator (Table A2 in Appendix A) and different measure of productivity growth (TFP and output per worker).
[24] This interpretation fits well with institutional features of the US labor market, in particular decentralized bargaining and flexible wage setting.
[25] Recall from section 2 on data that also the skill intensity of each macro occupation varies across sectors as the employment shares of each elementary SOC occupation vary by sector. Note that macro-occupations are an aggregate of elementary SOC occupations.

two main specifications for wages: the baseline model with industry fixed effects, but without dynamics (Models 1-3), and our favourite dynamic specification, estimated with system GMM (Models 4-6). Here we instrument the lagged dependent variable, occupational-specific level of *NR intensity* and its share of employment. Again, all variables are in log to interpret the effects in terms of elasticity.

Model 1-3 in Table 5 shows that the effect of *NR intensity* is positive and statistically significant across all the occupational groups. However, the estimated elasticity is decreasing in the occupational ranking, and is significantly lower for LS occupations. Also, *Emp HS* has a positive wage effect for clerks (p-value=0.10) and even more so for lower occupations. Conversely, *Emp MS* is associated with a statistically significant wage penalty for all occupational groups. The effect of *Cap Equip* is not in line with our previous findings on skill demand: equipment magnifies the wage gap between HS and MS occupations relative to LS. The effect of trade is statistically insignificant for HS and MS occupations, while it is negative for LS ones where the coefficient of *Imp Pen Hi-Med* is also statistically significant.

Table 5 ABOUT HERE

Models 4-6 in Table 5 are our favourite dynamic specifications. The first noticeable difference with the static model is that the effect of *NR intensity* remains statistically different from zero only for HS occupations. The effect is also quite large with elasticity equal to 0.45 in the short-term and 2.1 in the long-term. The coefficient associated with the employment share of HS is now positive and significant only for HS and MS, while that of LS disappears. In general, the effects of Non-Routine skills on wages appear to increase with occupational quality. Similar to what was observed for the determinants of *NR intensity*, wage persistence is instead decreasing in occupational quality.

Compared to Models 1-3 the new specifications yield clearer results for the remaining explanatory variables. *Cap Equip* has a positive wage effect on all occupations. While the short-run elasticity seems only slightly higher for LS occupations, the long-term effect is much higher: 0.13 compared to 0.04 for HS and MS occupations. Trade with high- and medium-wage countries is associated with a higher wage premium for high-skill occupations, consistent with our findings for *NR intensity*. The effect is modest but not small with a long-term elasticity of 0.23. Finally, *Imp Pen Low* has a near significant (p-value=0.152) negative effect only on low-skilled workers, which sum up to a long-term elasticity of 0.33. However, similar to what we remarked with regards to productivity, the effects of trade on wages are not very robust to the use of the BE estimator, while the other variables remain qualitatively unaffected (Table A3 in online Appendix A).

The modest and unclear wage effect of trade is accounted by two effects that tend to cancel out at the macro-level. On the one hand a contraction in employment entails a selection effect that favors the survival of the best workers and increases their average productivity and hence wage. On the other hand lower bargaining power compresses the wages of continuing workers. By and large, these findings are in line with other industry-level studies showing that trade competition has had little impact on US manufacturing wages (Edwards and Lawrence, 2010; Ebenstein et al., 2013).

7. Concluding remarks and future research

This paper has elaborated an empirical analysis of changes in the skill content of occupations in US manufacturing industries over the period 1999-2010. Following the seminal work of Autor, Levy and Murnane (2003) we adopt a task-based approach to analyze the determinants and the effects of changes in the demand of Non-Routine skills. The ALM study and the literature that followed conclude that the diffusion of computing technology in the 1990s augmented the productivity of occupations intensive in interactive and analytical skills to the detriment of occupations intensive in routine skills. Such a process, in turn, gave way to significant divergence within and between occupations and industries. The first goal of the paper was to assess whether technology continued to be a source of divergence throughout the 2000s. At the same time we acknowledge the prominence of other global forces, in particular the remarkable transformation of the global import-export matrix due to the expansion of international trade with China and other emerging economies. Accordingly, the second goal of the paper was to gauge the impact of trade on the skill content of US occupations and industries after the uptake of trade with low-wage and emerging countries.

Our analysis yields three main results. First, import competition from low-wage countries has induced skill adaptation in low-skill industries that are arguably more exposed to foreign competition. In general, trade emerges as a stronger driver of demand for Non-Routine skills than technology through the 2000s. The second key finding is that both technology and import from low-wage countries have induced skill convergence across industries but not owing to convergence across occupations. Indeed, both technology and trade with low-wage countries induce stronger skill upgrading for high- and low-skill occupations, and therefore a polarization effect. The last result is in line with previous literature and confirms that higher Non-Routine skills have overall modest effects on both productivity and wages except for High-Skill occupations.

Looking ahead, the limitations and omissions of this study are a compass for future research on these issues. To keep things simple, we opted for an admittedly uncomplicated portrayal of technology which leaves plenty of room for a richer characterization. One step in this direction is the exploration of a notion that is just mentioned but not fully developed here, namely that technology evolves and that different stages of the life-cycle influence significantly the relevance of know-how and skills required to use them (Vona and Consoli, 2015). Another promising departure from the present paper would be the analysis of the origin of new educational programs. In a truly dynamic process, the short-run imbalances triggered by trade and technology on the demand for skills are expected to stimulate the creation of educational packages aimed at facilitating the diffusion of the new skills. In this spirit, our future research will focus on the evolution of formal education and training in response to changing demand for skills.

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Table 1: Summary statistics for the pooled sample

Variable	Mean	SD	25th percentile	50th percentile	75th percentile	Min	Max	N. of Obs.	Reference period	Source
Dependent variables										
NR intensity	0.932	0.111	0.844	0.934	1.009	0.708	1.309	1008	1999-2010	O-NET
NR intensity HS	1.27	0.033	1.255	1.269	1.286	1.094	1.379	1008	1999-2010	O-NET
NR intensity MS	1.121	0.059	1.069	1.122	1.173	0.928	1.286	1008	1999-2010	O-NET
NR intensity LS	0.788	0.107	0.678	0.794	0.893	0.614	0.991	1001	1999-2010	O-NET
Wage HS	30.936	4.152	28.155	30.562	33.342	16.911	49.93	1008	1999-2010	O-NET
Wage MS	17.645	2.68	15.85	17.604	19.31	10.794	30.64	1008	1999-2010	O-NET
Wage LS	13.856	2.706	12.092	13.84	15.262	8.179	25.289	1001	1999-2010	O-NET
Value added per worker	133.686	127.871	76.203	101.298	139.392	40.919	1850.1	1032	1998-2009	NBER-CES
Main variables										
Cap Equip	0.081	0.097	0.032	0.059	0.082	0.007	0.816	1032	1998-2009	NBER-CES
Imp Pen Hi-Med	0.184	0.114	0.106	0.177	0.23	0.011	0.983	1007	1996-2007	Schott
Imp Pen Low	0.063	0.086	0.01	0.024	0.098	0	0.645	1007	1996-2007	Schott
Imp Pen China	0.046	0.057	0.007	0.02	0.071	0	0.601	1007	1996-2007	Schott
Imp Pen Low No China	0.017	0.041	0.001	0.003	0.01	0	0.22	1007	1996-2007	Schott
Controls										
Emp Sh HS	0.2	0.125	0.119	0.158	0.203	0.066	0.743	922	1998-2009	O-NET
Emp Sh MS	0.155	0.056	0.113	0.145	0.194	0.034	0.329	922	1998-2009	O-NET
Distance to frontier	91.389	7.775	90.742	93.567	94.738	0	97.507	1032	1998-2009	NBER-CES
High Tech	0.14	0.347	0	0	0	0	1	1032	1999-2010	Eurostat
Med Tech	0.195	0.396	0	0	0	0	1	1032	1999-2010	Eurostat
Low Tech	0.545	0.498	0	1	1	0	1	1032	1999-2010	Eurostat

Notes: All statistics are weighted by average employment share over the period 1999-2010. Non-routine skill intensity, wage and employment share variables have missing information for the period 1999-2001 pertaining to the following industries: Other Food (3119); Apparel Accessories and Other Apparel (3159); Sawmills and Wood Preservation (3211); Lime and Gypsum Product (3274); Iron and Steel Mills and Ferroalloy (3311); Cutlery and Handtool (3322); Motor Vehicle (3361); Other Furniture Related Product (3379). NR intensity LS and Wage LS have additional missing values: Railroad Rolling Stock (3365) in 2003, Other Leather and Allied Product (3169) and Leather and Hide Tanning and Finishing (3161) in the period 2008-2010. Information for employment share variables is missing for the year 1998. Import penetration variables have missing values in the period 1996-2007for the following industries: Apparel Knitting Mills (3151); Coating, Engraving, Heat Treating, and Allied Activities (3328). For year 2007 we additionally miss information for Manufacturing and Reproducing Magnetic and Optical Media (3346).

Table 2: Effects of Import Competition and Technology on Non-Routine Skill Intensity

Dependent Variable: NR Intensity

Model	[1]	[2]	[3]	[3a]	[3b]	[3c]	[3d]
NR Intensity -1	0.9090***	0.9061***	0.9153***	0.9495***	0.8894***	0.9059***	0.8960***
	[0.023]	[0.025]	[0.023]	[0.015]	[0.048]	[0.061]	[0.038]
Cap Equip -1	0.0108	0.0116	0.0242**	0.0058*	0.0369	0.0262***	0.0045
	[0.011]	[0.012]	[0.010]	[0.003]	[0.049]	[0.010]	[0.009]
Imp Pen Hi-Med -3		0.0122*	-0.0068	-0.0065	-0.0023	-0.0263***	0.0327
		[0.007]	[0.008]	[0.007]	[0.014]	[0.008]	[0.022]
Imp Pen Low -3			0.0445***	0.0081	0.0442***	0.0590***	0.0499
			[0.008]	[0.049]	[0.010]	[0.010]	[0.039]
Med Tech	-0.0032	-0.0031	-0.0052**	-0.0032	-0.0065***		
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]		
Low Tech	-0.0099***	-0.0093***	-0.0108***	-0.0050**	-0.0126***		
	[0.003]	[0.002]	[0.002]	[0.002]	[0.003]		
Observations	922	899	899	447	452	436	463
N. of groups	86	84	84	42	42	41	43
AR2	-0.1049	-0.0886	-0.1391	-0.8143	0.181	-1.1537	1.5728
AR2 crit. prob.	0.9164	0.9294	0.8893	0.4155	0.8564	0.2486	0.1158
Hansen J	69.7197	66.6347	64.7033	31.3199	34.0926	31.8397	35.6693
Hansen df	63	63	63	28	28	27	28
Hansen crit. prob.	0.2619	0.3531	0.417	0.3031	0.1978	0.2381	0.1512
Instruments	78	79	80	45	45	42	43

Notes: System GMM with Windmeijer correction for standard errors. The dependent variable is Non-Routine Skill Intensity and is an index of industry-level Non-Routine task intensity computed as: (sum of industry Non-Routine cognitive and interactive task inputs)/(sum of routine and manual task inputs). Specifications [3a] and [3b] include the sample split between industries with respectively below and above- median value of import penetration from low wage countries in the pre-sample period 1989-1995. Specifications [3c] and [3d] include the sample split between industries with respectively below and above- median value of NR Intensity for the initial year 2002. Med Tech=Medium-Tech dummy; Low Tech=Low-Tech dummy. All regressions are weighted by average employment share over the period 1999-2010. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level. Coefficients for the regression constant and year effects are not reported for sake of simplicity.

Table 3: Effects of Import Competition and Technology on Non-Routine Skill Intensity in three occupational groups (High-Skill, Medium-Skill and Low-Skill)

Dependent Variable: NR intensity	HS	MS	LS	HS	MS	LS
Model	[1]	[2]	[3]	[4]	[5]	[6]
NR Intensity HS -1	0.8164***			0.8155***		
	[0.036]			[0.037]		
NR Intensity MS -1		0.9257***			0.9195***	
		[0.035]			[0.037]	
NR Intensity LS -1			0.9187***			0.9179***
			[0.012]			[0.012]
Cap Equip -1	0.0098*	0.0035	0.0101***	0.0093*	0.0035	0.0118***
	[0.005]	[0.004]	[0.004]	[0.005]	[0.004]	[0.003]
Imp Pen Hi-Med -3	0.0012	0.0059*	-0.0090**	0.0032	0.0078**	-0.0241***
	[0.006]	[0.003]	[0.005]	[0.008]	[0.004]	[0.007]
Imp Pen Low -3	0.0484***	0.0029	0.0249**			
	[0.008]	[0.006]	[0.010]			
Imp Pen China -3				0.0542***	0.0109	0.0027
				[0.020]	[0.014]	[0.013]
Imp Pen Low No China -3				0.0355	-0.0138	0.0822***
				[0.028]	[0.015]	[0.019]
Med Tech	-0.0007	-0.0001	-0.0003	-0.0007	-0.0003	-0.0006
	[0.004]	[0.001]	[0.001]	[0.004]	[0.001]	[0.001]
Low Tech	-0.0031	-0.0011**	-0.0006	-0.0027	-0.0006	-0.0029*
	[0.003]	[0.000]	[0.001]	[0.003]	[0.001]	[0.002]
Observations	899	899	891	899	899	891
N. of groups	84	84	84	84	84	84
AR2	0.2555	0.1217	1.2625	0.2531	0.1119	1.2311
AR2 crit. prob.	0.7983	0.9031	0.2068	0.8002	0.9109	0.2183
Hansen J	63.1799	67.2388	67.2271	63.2206	68.2538	65.5312
Hansen df	58	58	58	58	58	57
Hansen crit. prob.	0.2985	0.1902	0.1904	0.2972	0.168	0.205
Instruments	75	75	75	76	76	75

Notes: System GMM with Windmeijer correction for standard errors. The dependent variable is Non-Routine Skill Intensity and is an index of industry-level Non-Routine task intensity computed as: (sum of industry Non-Routine cognitive and interactive task inputs)/(sum of routine and manual task inputs). The dependent variable has been computed for three different groups of professions: HS=High-Skill; MS=Middle-Skill; LS=Low-Skill. Med Tech=Medium-Tech dummy; Low Tech=Low-Tech dummy. All regressions are weighted by average employment share over the period 1999-2010. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level. Coefficients for the regression constant and year effects are not reported for sake of simplicity.

Table 4: Effects of Non-Routine Skill Intensity on Productivity

Dependent Variable: Change in the log of value added per worker

Model	[1]	[2]	[2a]	[2b]	[3]
Distance to frontier -1	0.0679*	0.0770**	0.1368*	-0.3657	0.1657**
	[0.035]	[0.036]	[0.068]	[0.470]	[0.078]
NR Intensity -1	0.1861***	-0.0783	-0.2533	-0.5309*	-0.2768
	[0.062]	[0.139]	[0.310]	[0.289]	[0.181]
Emp Sh HS -1		0.1460**	0.1638*	0.3195*	0.2164**
		[0.068]	[0.094]	[0.172]	[0.088]
Emp Sh MS -1		0.0993*	0.0408	0.1230*	0.2470**
		[0.055]	[0.102]	[0.072]	[0.123]
Cap Equip -1					0.0122**
					[0.006]
Imp Pen Hi-Med -2					-0.007
					[0.066]
Imp Pen Low -2					-0.1403
					[0.109]
Med Tech	0.0027	0.0054	0.0062	0.0104	0.0117
	[0.007]	[0.009]	[0.008]	[0.010]	[0.017]
Low Tech	0.0066	0.0133*	0.0290**	0.0029	0.0232*
	[0.007]	[0.007]	[0.014]	[0.010]	[0.013]
Observations	836	836	418	418	815
N. of groups	86	86	43	43	84
AR2	0.4831	0.4525	2.2637	-1.2226	0.504
AR2 crit. prob.	0.629	0.6509	0.0236	0.2215	0.6142
Hansen J	39.8713	41.1725	29.7869	30.706	47.9372
Hansen df	36	36	27	27	45
Hansen crit. prob.	0.3019	0.2545	0.3238	0.2834	0.3545
Instruments	50	52	43	43	64

Notes: System GMM with Windmeijer correction for standard errors. Med Tech=Medium-Tech dummy; Low Tech=Low-Tech dummy. All covariates, except dummies, have been log-transformed. Specifications [2a] and [2b] include the sample split between industries with respectively below and above- median value of log value added in the pre-sample period 1990-1998. All regressions are weighted by average employment share over the period 1999-2010. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level. Coefficients for the regression constant and year effects are not reported for sake of simplicity.

Table 5: Effects of Non-Routine Skill Intensity on Wage

Dependent Variable: Log(Hourly Wage+1)						
Model	[1]	[2]	[3]	[4]	[5]	[6]
Emp Sh HS -1	0.1455	0.2434	0.3964***	0.1714***	0.1221**	0.002
	[0.187]	[0.147]	[0.105]	[0.054]	[0.061]	[0.039]
Emp Sh MS -1	-0.4497***	-0.2149*	-0.3375**	0.0139	-0.0494	-0.0457
	[0.101]	[0.116]	[0.137]	[0.032]	[0.047]	[0.051]
Cap Equip -1	0.0301	0.0619***	0.0115	0.0092***	0.0092**	0.0120***
	[0.021]	[0.020]	[0.011]	[0.003]	[0.005]	[0.004]
Imp Pen Hi-Med -3	-0.0375	-0.0625	-0.1685**	0.0518**	0.003	-0.0092
	[0.077]	[0.091]	[0.081]	[0.021]	[0.024]	[0.017]
Imp Pen Low -3	-0.0428	0.1189	-0.0786	0.0224	0.0397	-0.0306
	[0.065]	[0.113]	[0.087]	[0.018]	[0.029]	[0.021]
NR Intensity HS -1	1.4716***			0.4562**		
	[0.360]			[0.205]		
NR Intensity MS -1		1.2772***			0.0786	
		[0.300]			[0.382]	
NR Intensity LS -1			0.3094*			-0.081
			[0.156]			[0.057]
Wage HS -1				0.7830***		
				[0.071]		
Wage MS -1					0.8007***	
					[0.081]	
Wage LS -1						0.9091***
						[0.034]
Med Tech				0.0111***	-0.0066	0.0008
				[0.004]	[0.006]	[0.004]
Low Tech				0.0205***	-0.0066	-0.0085
				[0.007]	[0.008]	[0.008]
Observations	899	899	891	899	899	891
N. of groups	84	84	84	84	84	84
R-sq	0.9412	0.9351	0.9148			
AR2				-0.6022	1.4027	-0.2476
AR2 crit. prob.				0.547	0.1607	0.8044
Hansen J				59.3226	54.8066	33.0889
Hansen df				57	57	37
Hansen crit. prob.				0.3909	0.5578	0.653
Instruments				77	77	57

Notes: Models from [1] to [3] are panel data regressions with fixed effects and robust standard errors adjusted for clustering at the industry level. Models [4]-[6] are System GMM with Windmeijer correction for standard errors. The dependent variable is log of hourly wage and has been computed for three different groups of professions: HS=High-Skill; MS=Middle-Skill; LS=Low-Skill. Med Tech=Medium-Tech dummy; Low Tech=Low-Tech dummy. All covariates, except dummies, have been log-transformed. All regressions are weighted by average employment share over the period 1999-2010. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level. Coefficients for the regression constant and year effects are not reported for sake of simplicity.

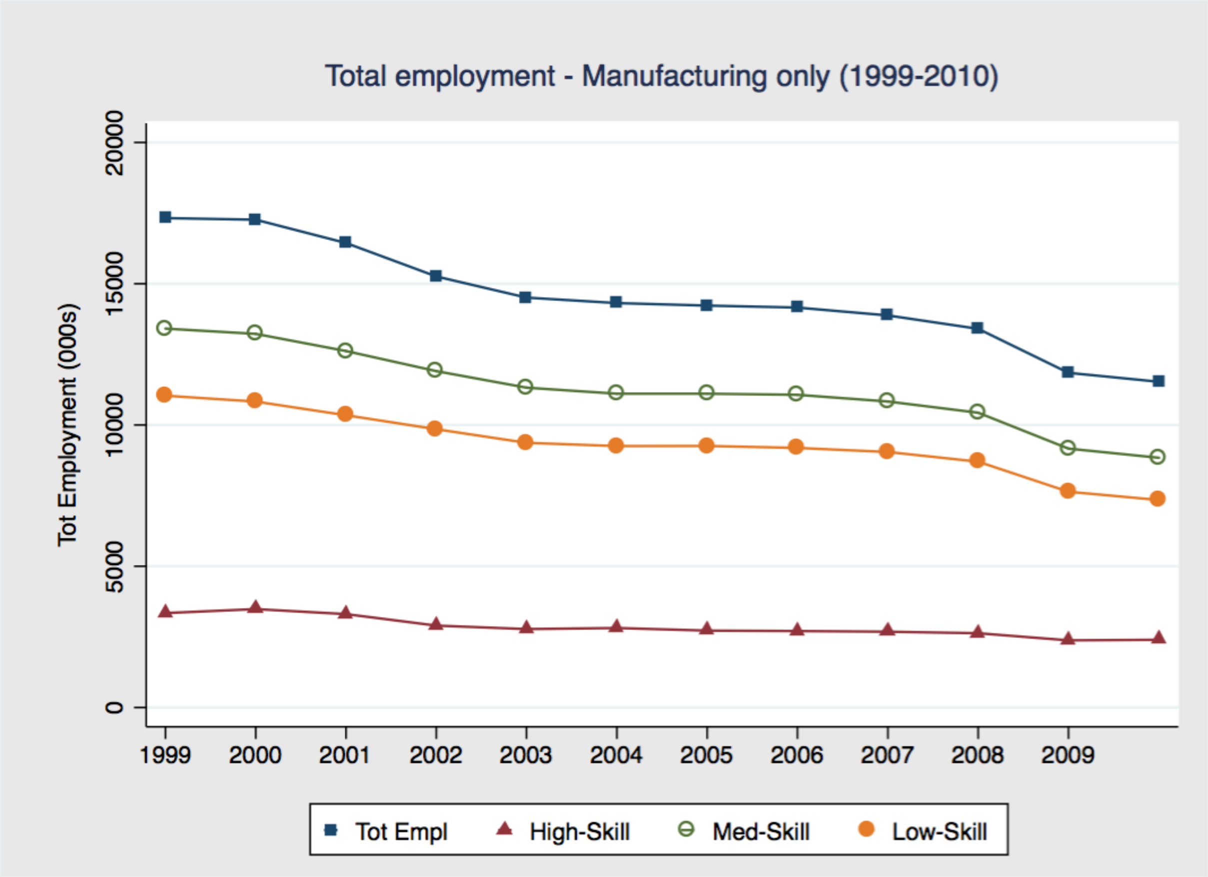
Total employment - Manufacturing only (1999-2010)
Tot Employment (000s)
0
5000
10000
15000
20000
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
Tot Empl
High-Skill
Med-Skill
Low-Skill

Figure 1

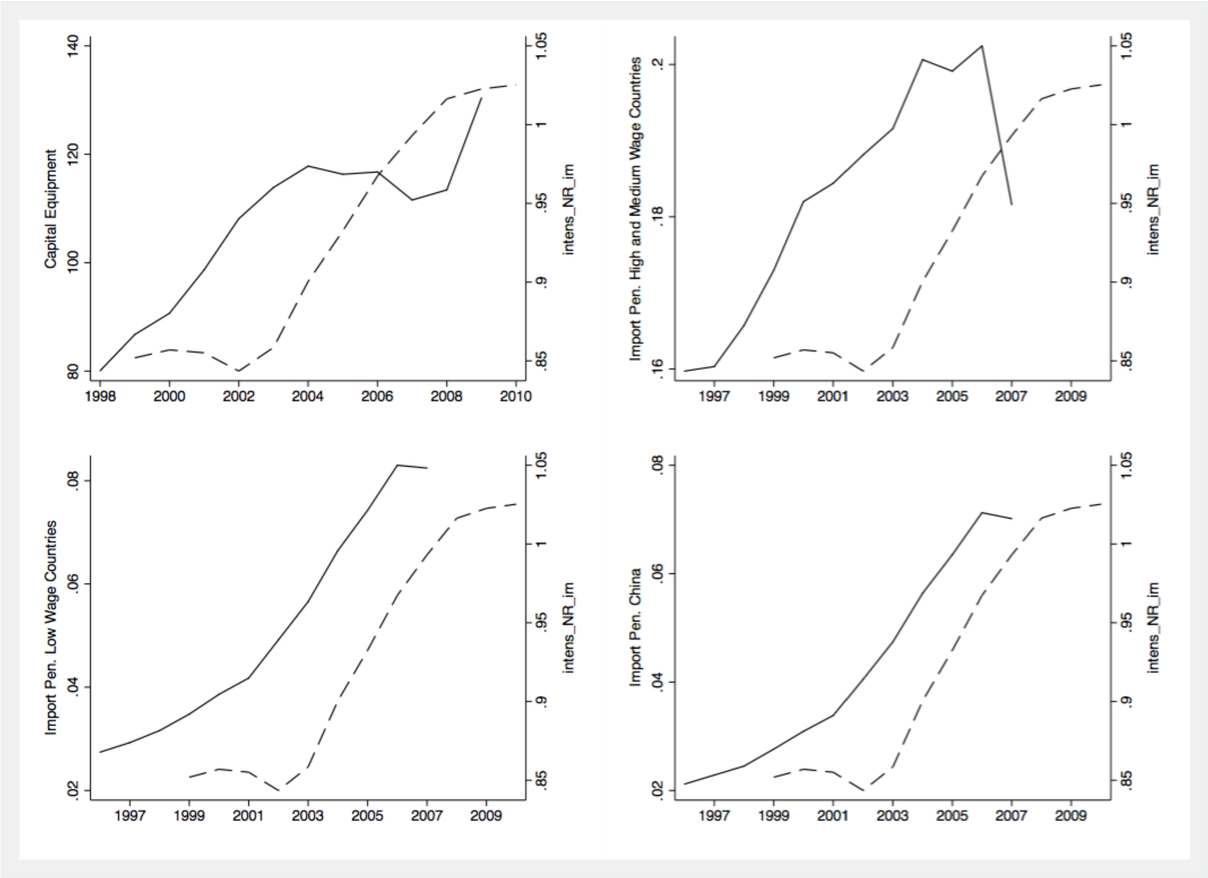
Capital Equipment
intens_NR_im
Import Pen. High and Medium Wage Countries
Import Pen. Low Wage Countries
Import Pen. China

Figure 2

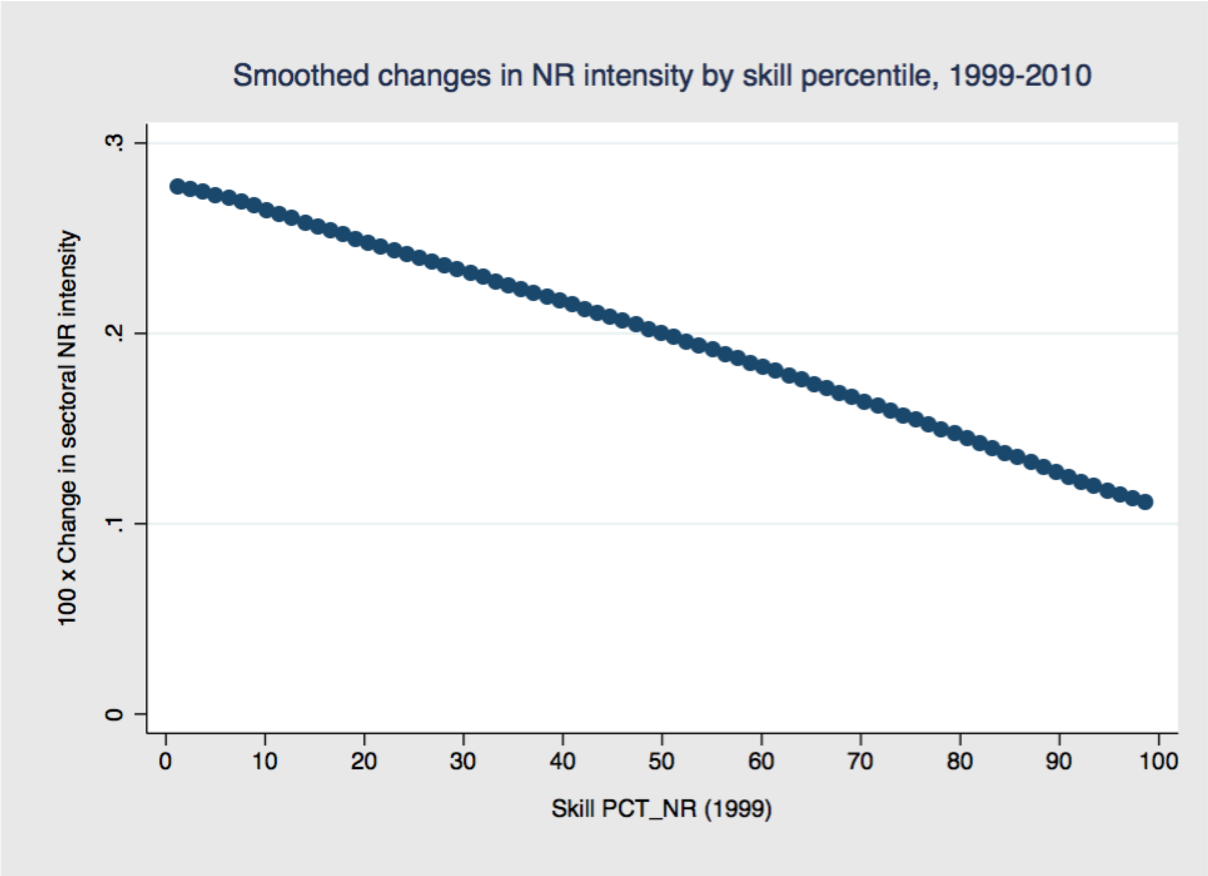
Smoothed changes in NR intensity by skill percentile, 1999-2010
100 x Change in sectoral NR intensity
0
.1
.2
.3
0
10
20
30
40
50
60
70
80
90
100
Skill PCT_NR (1999)

Figure 3

Appendix A: Robustness checks

Appendix A reports four main robustness checks to test our results under different specifications and estimation methods. First, we show how results are clearly affected by the use of a dynamic specification. Table A1 estimates the main specifications of Table 3 in the main text (Model 1 and 3) using OLS and FE without the lagged dependent variable. These results lead us to conclude that a dynamic specification reduces the bias of the estimated effects, especially for capital equipment. Second, Hauk and Wacziarg (2009) recently showed that in presence of large measurement errors a between-estimator (BE) reduces the bias in estimated coefficients as compared to a system-GMM estimator.[1] On the basis of this, we use a BE estimator to carry out a robustness check by regressing the dependent variable at time t over itself at time t-k and a time-averaged explanatory over t and t-k. Table A2 and Table A3 report results of the robustness checks for non-routine skill intensity and productivity and wage respectively. Results reported in the main text are robust to this alternative estimation method. Third, our measure of non-routine skill intensity comprises changes in the employment shares between occupations and changes in Non-Routine skills within occupation. As a further robustness check we re-estimate our main specifications (Table 3, columns [3], [3c] and [3d]) by "switching off" the within-variation of Non-Routine skill intensity. In practice, we keep the task level of each occupation at the mean value for the whole period (1999-2010) and we aggregate our task constructs at the industry level by letting only the employment shares at the industry-occupation level to change. Results are shown in Table A4 and are coherent with results reported in the main text. Overall, specification [1] (equivalent to our preferred specification [3] of Table 3 in the main text)

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[1] Comprehensive Montecarlo evidence provided in Hauk and Wacziarg (2009) shows that the measurement error bias and unobservable heterogeneity bias mutually offset each other when using simple between-estimator. In turn, as the measurement error increases, estimators that account for unobservable heterogeneity (such as FE or dynamic GMM) become less precise in estimating the parameters of interest. System GMM, however, remains relatively more robust than differenced-GMM and FE estimators.

confirms our main results. Specifications [1a] and [1b] (equivalent to specifications [3c] and [3d] of Table 3) confirm our results as well, although the level of significance of coefficients is reduced due to the lower overall variation. Lastly, to gain further insights on the substantial heterogeneity in the effect of trade and technology across occupational groups as arising from Table 3, Figure Figure A1 and Figure A2 report the 95% confidence intervals for the estimated coefficients and interpret non-overlapping confidence intervals as indicating statistically significant differences. Figure A1 shows the estimated coefficients and 95% confidence intervals for specifications 1 through 3 of Table 3: the only significant difference is between lower and middle occupations for *Imp Pen Hi-Med*. Figure A2 reports coefficients and 95% confidence intervals for model specifications 4 through 6 of Table 3: here significant differences are found between low and middle occupations for both import penetration from high and low wage countries. On the whole, this corroborates our results on the role of *Imp Pen Hi-Med* as a source of skill inequality between low and middle skill occupations, while *Imp Pen Low* has an opposite equalizing effect.

Table A1: Effects of Import Competition and Technology on Non-Routine Skill Intensity – static models

Dependent Variable: NR Intensity

Model	[1a]	[1b]	[2a]	[2b]
Cap Equip -1	0.2452***	-0.1801*	0.2156***	-0.2006*
	[0.053]	[0.092]	[0.055]	[0.107]
Imp Pen Hi-Med -3			0.091	-0.032
			[0.091]	[0.073]
Imp Pen Low -3			-0.1382	0.3267***
			[0.148]	[0.054]
Med Tech	0.0016		0.0099	
	[0.049]		[0.051]	
Low Tech	-0.1062***		-0.0972***	
	[0.030]		[0.031]	
Observations	1008	1008	983	983
N. of groups		86		84
R-sq	0.7199	0.9254	0.7254	0.9416

Notes: The Dependent Variable is Non-Routine Skill Intensity and is an index of industry-level non-routine task intensity computed as: (sum of industry non-routine cognitive and interactive task inputs)/(sum of routine and manual task inputs). Specifications [1a] and [2a] have been estimated via OLS. Specifications [1b] and [2b] have been estimated with fixed effects. MedTech=Medium-Tech dummy; LowTech=Low-Tech dummy. All regressions are weighted by average employment share over the period 1999-2010. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level. Coefficients for the regression constant and year effects are not reported for sake of simplicity.

Table A2: Effects of Import Competition and Technology on Non-Routine Skill Intensity – between estimator

Dependent Variable: NR Intensity 2006-2010

Model	Overall	HS	MS	LS
NR Intensity 1999-2002	0.7166***			
	[0.040]			
NR Intensity HS 1999-2002		0.6216***		
		[0.168]		
NR Intensity MS 1999-2002			0.7920***	
			[0.124]	
NR Intensity LS 1999-2002				0.3486***
				[0.051]
Cap Equip 1999-2002	0.0232	0.0191	-0.0019	0.0656***
	[0.018]	[0.022]	[0.022]	[0.012]
Imp Pen Hi-Med 1999-2002	-0.0447**	0.0555**	0.0483**	-0.0224
	[0.020]	[0.028]	[0.020]	[0.019]
Imp Pen Low 1999-2002	0.1771***			
	[0.036]			
Imp Pen Low No China 1999-2002		0.0807	0.0132	0.2132***
		[0.090]	[0.066]	[0.064]
Imp Pen China 1999-2002		0.0024	0.0149	-0.0856**
		[0.064]	[0.058]	[0.039]
Med Tech	-0.0142**	0.0023	-0.0042	0.0051
	[0.006]	[0.012]	[0.008]	[0.005]
Low Tech	-0.0180***	-0.0103	-0.0051	-0.0029
	[0.005]	[0.008]	[0.003]	[0.006]
Observations	84	84	84	84
R-sq	0.9517	0.6362	0.6543	0.7665

Notes: The Dependent Variable is Non-Routine Skill Intensity and is an index of industry-level non-routine task intensity computed as: (sum of industry non-routine cognitive and interactive task inputs)/(sum of routine and manual task inputs) for the period 2006-2010. The Dependent Variable has been also computed for three different groups of professions: HS=High-Skill; MS=Middle-Skill; LS=Low-Skill. Med Tech=Medium-Tech dummy; Low Tech=Low-Tech dummy. All regressions are weighted by average employment share over the period 1999-2010. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level. Robust standard errors adjusted for clustering at the industry level. Coefficient for the regression constant is not reported for sake of simplicity.

Table A3: Effects of Non-Routine Skill Intensity on Productivity and Wage – between estimator

Dependent Variable:	Log(Value added per worker) 2006-2010	Log(Hourly Wage+1) 2006-2010		
Model		HS	MS	LS
Value added per worker 1999-2002	1.0636***			
	[0.063]			
NR Intensity 1999-2002	-0.9927			
	[1.188]			
Wage HS 1999-2002		0.4731***		
		[0.108]		
NR intensity HS 1999-2002		2.4887***		
		[0.643]		
Wage MS 1999-2002			0.8292***	
			[0.107]	
NR intensity MS 1999-2002			0.6709	
			[0.702]	
Wage LS 1999-2002				0.8323***
				[0.056]
NR intensity 1999-2002				-0.4705*
				[0.276]
Emp Share HS 1999-2002	1.2591**	0.4896***	0.2999***	0.1928**
	[0.492]	[0.090]	[0.084]	[0.083]
Emp Share MS 1999-2002	-0.2605	-0.0135	-0.1434	-0.3206**
	[0.409]	[0.111]	[0.137]	[0.126]
Cap Equip 1999-2002	0.0405	0.0303***	-0.0018	0.0226**
	[0.047]	[0.009]	[0.010]	[0.010]
Imp Pen Hi-Med 1999-2002	-0.4815*	0.2391***	0.1582**	-0.0219
	[0.262]	[0.066]	[0.077]	[0.059]
Imp Pen Low 1999-2002	0.9730**	0.1091	0.2824*	0.076
	[0.468]	[0.115]	[0.154]	[0.123]
Med Tech	0.0194	0.0237	-0.0066	0.0194
	[0.041]	[0.015]	[0.015]	[0.013]
Low Tech	0.0385	0.0514***	0.0242	-0.0073
	[0.042]	[0.016]	[0.017]	[0.013]
Observations	84	84	84	84
R-sq	0.959	0.9077	0.9044	0.9659

Notes: The Dependent Variable are value added per worker (column 1) and hourly wage (columns from 2 to 4) and all refer to period 2006-2010. Hourly wage is log transformed and has been computed for three different groups of professions: HS=High-Skill; MS=Middle-Skill; LS=Low-Skill. All covariates, except dummies, have been log-transformed. The Dependent Variable has been also computed for three different groups of professions: HS=High-Skill; MS=Middle-Skill; LS=Low-Skill. Med Tech=Medium-Tech dummy; Low Tech=Low-Tech dummy. All regressions are weighted by average employment share over the period 1999-2010. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level. Robust standard errors adjusted for clustering at the industry level. Coefficient for the regression constant is not reported for sake of simplicity.

Table A4: Effects of Import Competition and Technology on Non-Routine Skill Intensity – Task Time Invariant

Dependent Variable: NR Intensity

Model	[1]	[1a]	[1b]
NR Intensity -1	0.9115***	0.8443***	0.9424***
	[0.032]	[0.102]	[0.027]
Cap Equip -1	0.0211**	0.0255	0.0047
	[0.010]	[0.017]	[0.007]
Imp Pen Hi-Med -3	0.0034	-0.0124	0.0307*
	[0.010]	[0.009]	[0.016]
Imp Pen Low -3	0.0141*	0.0166	0.0596
	[0.008]	[0.012]	[0.047]
Med Tech	-0.0029		
	[0.003]		
Low Tech	-0.0130***		
	[0.002]		
Observations	899	433	466
N. of groups	84	41	43
AR2	0.7674	-0.5769	1.6328
AR2 crit. prob.	0.4429	0.564	0.1025
Hansen J	66.8158	25.3609	25.7477
Hansen df	63	27	28
Hansen crit. prob.	0.3474	0.5542	0.5869
Instruments	80	42	43

Notes: System GMM with Windmeijer correction for standard errors. The dependent variable is Non-Routine Skill Intensity and is an index of industry-level Non-Routine task intensity computed as: (sum of industry Non-Routine cognitive and interactive task inputs)/(sum of routine and manual task inputs). Within variation of task intensity is set equal to the mean value for the period 2002-2010. Specifications [1a] and [1b] include the sample split between industries with respectively below and above- median value of NR Intensity for the initial year 2002. Med Tech=Medium-Tech dummy; Low Tech=Low-Tech dummy. All regressions are weighted by average employment share over the period 1999-2010. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level. Coefficients for the regression constant and year effects are not reported for sake of simplicity.

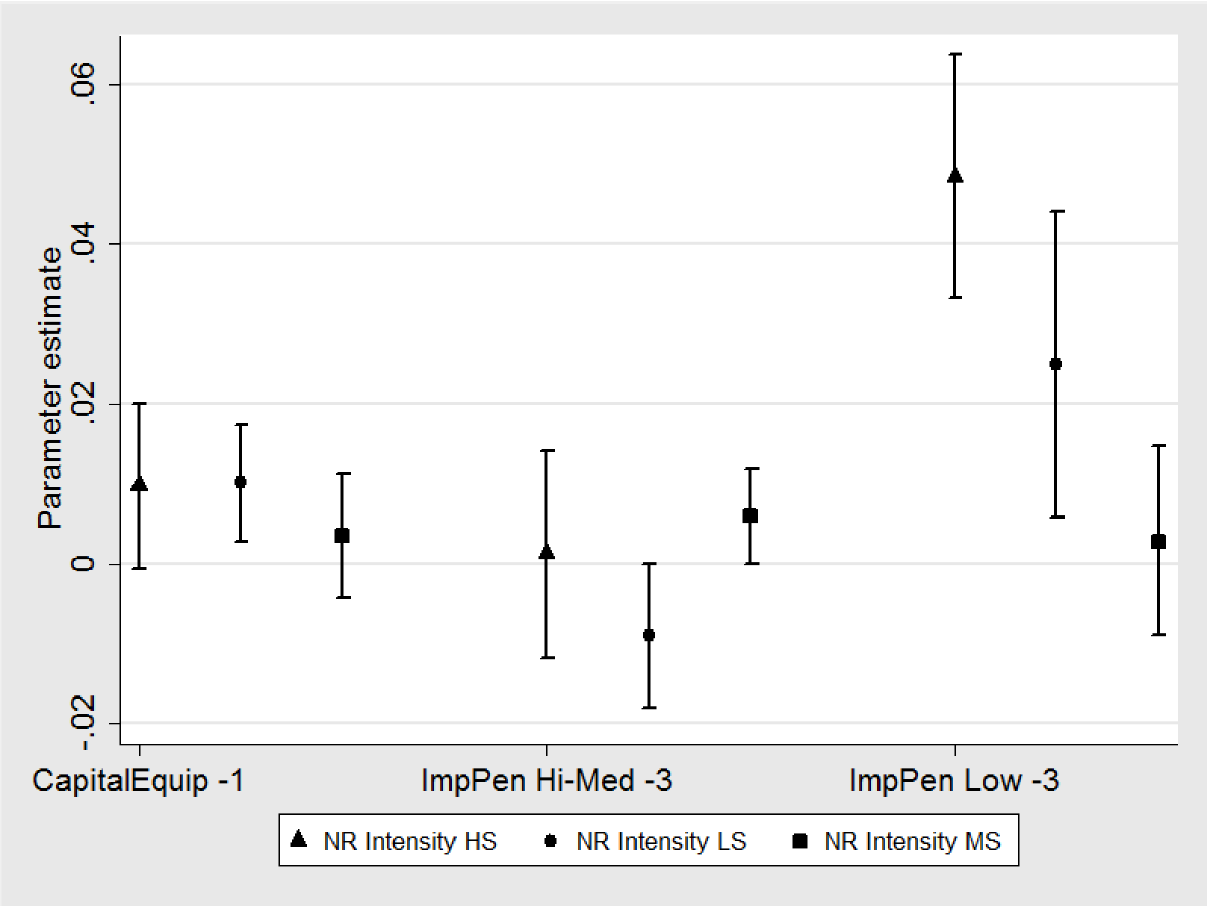

Figure A1: Coefficients with 95% confidence intervals from Table 3 Models 1 through 3.

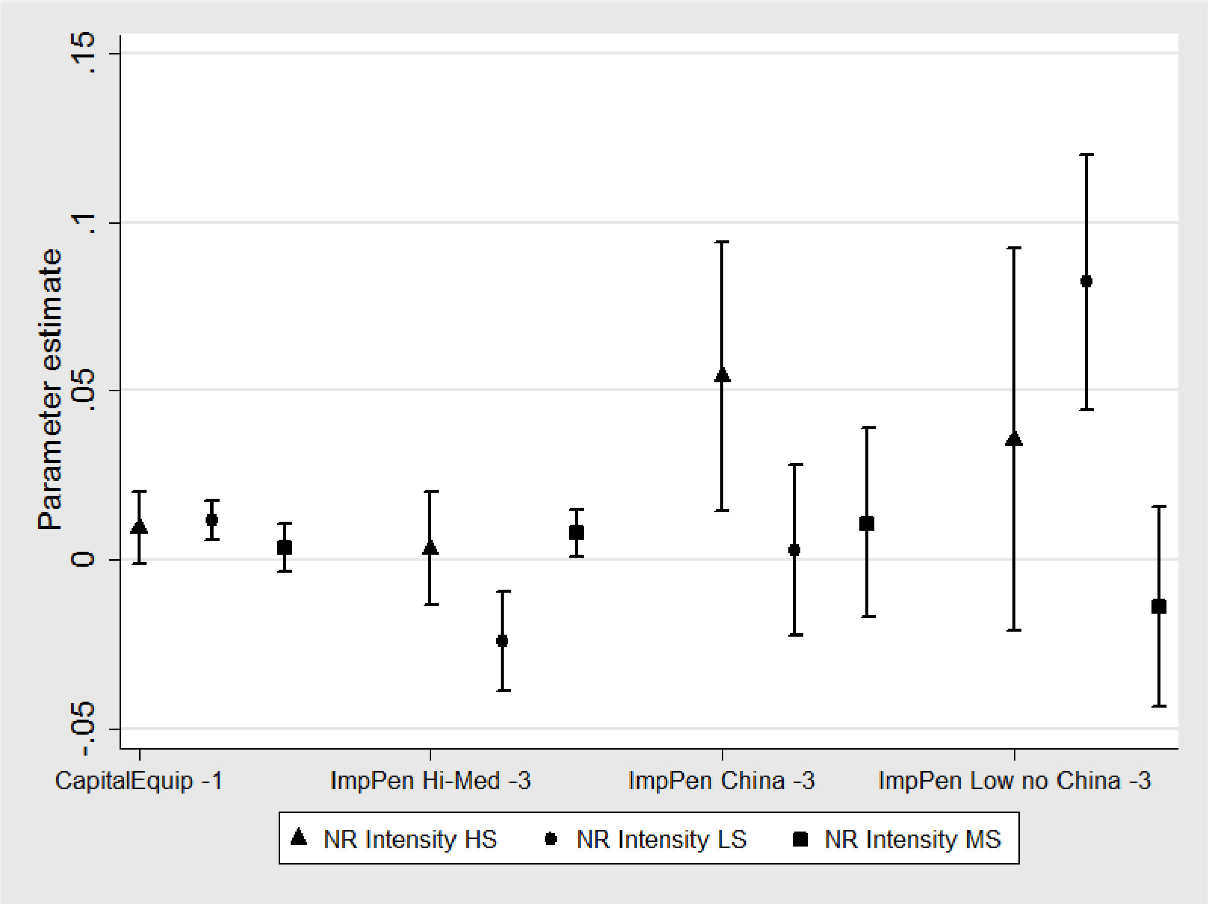

Figure A2: Coefficients with 95% confidence intervals from Table 3 Models 4 through 6.

Appendix B: Data appendix

B1. 1987 SIC – 2002 NAICS – 2007 NAICS Concordance

BLS data on employment for the period 1999-2010 encompasses different industry classification schemes: the 1987 Standard Industrial Classification (SIC1987), used until 2001, the 2002 North American Industry Classification System (NAICS), used until 2006, the 2007 North American Industry Classification System (NAICS), used thereafter. The switch between these schemes complicates the creation of a consistent set of industries for the purpose of comparison over time. To address this shortcoming we develop a new SIC1987-NAICS2002-NAICS2007 concordance to ensure that results are not driven by such changes. Starting with the standard 1987 SIC to 2002 NAICS and 2002 NAICS to 2007 NAICS concordances used by the U.S. Census Bureau[2], we manually create families of three-digit SIC and four-digit NAICS codes that group related SIC and NAICS categories together over time. We first map three-digit 1987 SIC codes into four-digit 2002 NAICS codes. We were able to link 78 out of 86 four-digit 2002 NAICS codes for manufacturing. We were unable to find a reliable match for 8 four-digit 2002 NAICS codes due to the existence of a better match of the corresponding three-digit 1987 SIC with other four-digit 2002 NAICS codes. For example, SIC code 342 "Cutlery, Handtools and General Hardware" could have fitted in both NAICS 3322 "Cutlery and Handtool" and 3325 "Hardware Manufacturing". We assigned it to the latter as we see a better fit among the different sub-classes. Due to the mismatch outlined above, non-routine skill intensity, wage and employment share variables have missing information for the period 1999-2001 pertaining to the following industries: Other Food (3119); Apparel Accessories and Other Apparel (3159); Sawmills and Wood Preservation (3211); Lime and Gypsum Product (3274); Iron and Steel Mills and Ferroalloy (3311); Cutlery and Handtool (3322); Motor Vehicle (3361); Other Furniture Related Product

[2] These concordances are available at http://www.census.gov/eos/www/naics/concordances/concordances.html

(3379). We then map four-digit 2007 NAICS codes into four-digit 2007 NAICS codes. Here we obtain a perfect match among the 86 manufacturing industries. The complete concordance table is available from the authors upon request.

B2. NBER-CES manufacturing database and Schott's trade data

Data on capital equipment per worker, value of US shipments and productivity per worker for the period 1989-2009 comes from the NBER-CES manufacturing industry database (Bartelsman and Gray, 1996; Becker and Gray, 2013). Data refers to the six-digit 1997 NAICS classification. Capital equipment has been deflated using industry-level price indexes of investments in the NBER-CES Manufacturing Industry database from Becker and Gray (2013). We use data on US imports and exports of the manufacturing industries from 1996 to 2007 as compiled by and discussed in Bernard et al. (2006). The most recent set of data have been retrieved by Peter Schott's website (available at http://faculty.som.yale.edu/peterschott/sub_international.htm) and refers to six-digit 1997 NAICS classification. We aggregate the information on all of these variables at the four-digit 1997 NAICS industry level weighting for the level of employment at six-digit. We use standard 1997 NAICS to 2002 NAICS and 2002 NAICS to 2007 NAICS concordances available from the U.S. Census Bureau to map manufacturing industries into an industry classification consistent with other available data. Trade data has missing values in the period 1996-2007 for the following industries: Apparel Knitting Mills (3151); Coating, Engraving, Heat Treating, and Allied Activities (3328). For year 2007 we additionally miss information for Manufacturing and Reproducing Magnetic and Optical Media (3346).

B3. O-NET and BLS employment data

The Occupational Information Network (O-NET) is a comprehensive database of worker attributes and job characteristics. As the replacement for the Dictionary of Occupational Titles (DOT), O-NET is the primary source of information about US job characteristics.

O-NET data are generated by means of questionnaires administered to job incumbents and occupational analysts. Information is freely available for download.[3] O-NET is organized according to a 'content' model that matches characteristics of occupations and of individuals. Overall there are five questionnaires, each concerning a particular dimension of job content and based on a specific rating scale Respondents are asked to assign a numerical score to the importance of the following job-specific characteristics: Skills, Knowledge (includes education, training and work style questions), Abilities, Generalized Work Activities, and Work Context.

The main variables of interest for this study are contained in the Work Context and in the Work Activities surveys (Autor et al, 2003). Respondents are asked to rate the importance of particular work activities and characteristics required by the job. This rating indicates the degree of importance a particular descriptor is to the occupation. The possible ratings range from "Not Important" (1) to "Extremely Important" (5). O-NET data is reported at the six-digit Standard Occupation Classification (SOC) level. As employment data from BLS are available only at the four-digit SOC occupation level, we aggregate O-NET six-digit SOC at the four-digit level. Each four-digit SOC occupation contains in this way the average importance value of the corresponding six-digit SOC occupations.

To keep up with the changing occupational landscape of the labour market, the taxonomy of occupations is periodically revised. We kept track of all revisions at occupational level over

[3] http://www.xwalkcenter.org/

the period 2002-2010 to control for the birth and death of occupations (http://www.onetcenter.org/dataPublication.html). In some cases, new occupations appear in O-NET but we have no information on tasks for them. In all the cases when we have missing task values from new occupations but non-missing value of employment from BLS, we assign the value of task of the following year (if non missing) to that SOC occupation.

Three of the work contexts – "face-to-face discussions", "physical proximity" and "structured versus unstructured work" – contained several missing values (2039 out of 7695 occupation-year observations). This problem was particularly severe for the 2002-2004 time period (almost 65% of missing occupation-year observations). We impute missing data for these three factors through a regression approach. In particular, we impute missing values with the fitted values obtained by regressing all the work activities and work context factors on each of the three work context factors above by year.

As a result of the procedure described above we created a unique dataset containing time-varying information for 855 four-digit SOC occupations for the period 2002-2010.

Our task constructs are built from a detailed examination of O-NET Work Activities and Work Context. We build upon and expand the task constructs of Autor, Levy and Murnane (2003). The chosen items are grouped together in four main categories: Non-Routine Cognitive (NRC), Non-Routine Interactive (NRI), Routine Cognitive (RC) and Routine Manual (RM). Table B1 below lists the 40 O-NET variables used in this study. The main task categories are computed by summing the score of importance for a particular SOC occupation. This procedure makes sense as each task construct comprises a combination of ten items with the same score range. We also follow Autor and Dorn (2013) and calculate additional task constructs that differentiate between three broad occupational groups: high skill occupations, medium skill occupations and low skill occupations. Table B2 below lists the occupations for each single group.

To derive the demand for skills across industries and occupations, we mapped employment data at the occupation-industry level into the 855 four-digit SOC occupations. Employment data that vary by four-digit SOC occupation and four-digit NAICS industry is available from BLS for the period 1999-2010. In so doing we can calculate an employment-weighted measure of skills by aggregating different task scores for each occupation at the four-digit NAICS industry level into which remaining data has been merged. As BLS data on employment for the period 1999-2010 encompasses the use of different industry classification schemes (1987 SIC for the period 1999-2001 and 2002 NAICS for the period 2002-2006 and 2007 NAICS for the period 2007-2010), we use the concordance table described in Section A1 to properly map employment data through time. BLS data on employment lacks information for the following four-digit 2007 NAICS industries: Railroad Rolling Stock (3365) in 2003 and Other Leather and Allied Product (3169) in the period 2008-2010. Since the first usable wave of O-NET is for 2002 we miss information on employee abilities in the period 1999-2001. To cope with that, we assign to period 1999-2001 time invariant information drawn from the 2002 wave of O-NET (Autor et al., 2003). At the end of this procedure we are left with a panel of 86 four-digit NAICS manufacturing industries during the 1999-2010 period.

Our results are robust to alternative definitions of our task variables. As a robustness check, we define our task variables in three alternative ways. First, we use the standard definition of task constructs provided in Acemoglu and Autor (2011) that encompasses the use of less Work Activities and Work Context items compared to our definition. A second route is creating a composite indicator of our intended constructs using local factor analysis. Yet another alternative measure is transforming our task constructs into percentile values corresponding to their rank in the 2002 distribution. In this way, all of the outcome measures may be interpreted as levels or changes in task input relative to the 2002 task distribution. Our results are robust to all these different definitions and are available from the authors upon request.

Table B1: Definition of skill measures

Non-Routine cognitive	Judging the Qualities of Things, Services, or People; Evaluating Information to Determine Compliance with Standards; Analyzing Data or Information; Making Decisions and Solving Problems; Thinking Creatively; Updating and Using Relevant Knowledge; Organizing, Planning, and Prioritizing Work; Interpreting the Meaning of Information for Others; Coordinating the Work and Activities of Others; Developing and Building Teams
Non-routine interactive	Communicating with Supervisors, Peers, or Subordinates; Communicating with Persons Outside Organization; Establishing and Maintaining Interpersonal Relationships; Selling or Influencing Others; Resolving Conflicts and Negotiating with Others; Training and Teaching Others; Guiding, Directing, and Motivating Subordinates; Coaching and Developing Others; Provide Consultation and Advice to Others; Coordinate or Lead Others
Routine cognitive	Monitor Processes, Materials, or Surroundings; Estimating the Quantifiable Characteristics of Products, Events, or Information; Scheduling Work and Activities; Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment; Documenting/Recording Information; Performing Administrative Activities; Monitoring and Controlling Resources; Importance of Being Exact or Accurate; Importance of Repeating Same Tasks; Structured versus Unstructured Work
Routine manual	Performing General Physical Activities; Handling and Moving Objects; Controlling Machines and Processes; Operating Vehicles, Mechanized Devices, or Equipment; Spend Time Standing; Spend Time Climbing Ladders, Scaffolds, or Poles; Spend Time Walking and Running; Degree of Automation; Spend Time Making Repetitive Motions; Pace Determined by Speed of Equipment

Table B2: Occupation groups

High Skill Occupations

Six-digit SOC code	**Occupation title**
11-1021	General and Operations Managers
11-2011	Advertising and Promotions Managers
11-2021	Marketing Managers
11-2022	Sales Managers
11-2031	Public Relations Managers
11-3011	Administrative Services Managers
11-3021	Computer and Information Systems Managers
11-3031	Financial Managers
11-3040	Human Resources Managers
11-3041	Compensation and benefits managers
11-3042	Training and development managers
11-3049	Human resources managers, all other
11-3051	Industrial Production Managers
11-3061	Purchasing Managers
11-3111	Compensation and Benefits Managers
11-3121	Human Resources Managers
11-3131	Training and Development Managers
11-9011	Farm, Ranch, and Other Agricultural Managers
11-9013	Farmers, Ranchers, and Other Agricultural Managers
11-9021	Construction Managers
11-9041	Engineering Managers
11-9051	Food Service Managers
11-9071	Gaming Managers
11-9081	Lodging Managers
11-9111	Medical and Health Services Managers
11-9121	Natural Sciences Managers
11-9141	Property, Real Estate, and Community Association Managers
11-9151	Social and Community Service Managers
11-9199	Managers, All Other
13-1011	Agents and Business Managers of Artists, Performers, and Athletes
13-1031	Claims Adjusters, Examiners, and Investigators
13-1051	Cost Estimators
13-1081	Logisticians
13-1151	Training and Development Specialists
19-3032	Industrial-Organizational Psychologists

21-1011	Substance Abuse and Behavioral Disorder Counselors
21-1012	Educational, Vocational, and School Counselors
21-1013	Marriage and Family Therapists
21-1014	Mental Health Counselors
21-1015	Rehabilitation Counselors
21-1019	Counselors, All Other
21-1022	Medical and Public Health Social Workers
21-1091	Health Educators
23-1011	Lawyers
23-1022	Arbitrators, Mediators, and Conciliators
23-1023	Judges, Magistrate Judges, and Magistrates
23-2091	Court Reporters
23-2092	Law Clerks
23-2093	Title Examiners, Abstractors, and Searchers
23-2099	Legal Support Workers, All Other
25-1191	Graduate Teaching Assistants
25-2011	Preschool Teachers, Except Special Education
25-2012	Kindergarten Teachers, Except Special Education
25-2021	Elementary School Teachers, Except Special Education
25-2022	Middle School Teachers, Except Special and Vocational Education
25-2023	Vocational Education Teachers, Middle School
25-2041	Special Education Teachers, Preschool, Kindergarten, and Elementary School
25-2042	Special Education Teachers, Middle School
25-2053	Special Education Teachers, Middle School
25-3011	Adult Literacy, Remedial Education, and Ged Teachers and Instructors
25-3021	Self-Enrichment Education Teachers
25-3099	Teachers and instructors, all other
25-3999	Teachers and Instructors, All Other*
25-9031	Instructional Coordinators
27-1019	Artists and Related Workers, All Other
27-2011	Actors
27-2022	Coaches and Scouts
27-2023	Umpires, Referees, and Other Sports Officials
27-3010	Announcers
27-3011	Radio and Television Announcers
27-3012	Public Address System and Other Announcers
27-3022	Reporters and Correspondents
27-3031	Public Relations Specialists
27-3091	Interpreters and Translators
27-3099	Media and Communication Workers, All Other

29-9091	Athletic Trainers
45-1011	First-Line Supervisors/Managers of Farming, Fishing, and Forestry Workers
51-1011	First-Line Supervisors/Managers of Production and Operating Workers
53-1021	First-Line Supervisors/Managers of Helpers, Laborers, and Material Movers, Hand
53-1031	First-Line Supervisors/Managers of Transportation and Material-Moving Machine and Vehicle Operators
11-1011	Chief Executives
11-1031	Legislators
11-9031	Education Administrators, Preschool and Child Care Center/Program
11-9032	Education Administrators, Elementary and Secondary School
11-9033	Education Administrators, Postsecondary
11-9039	Education Administrators, All Other
11-9061	Funeral Directors
11-9131	Postmasters and Mail Superintendents
11-9161	Emergency Management Directors
13-1021	Purchasing Agents and Buyers, Farm Products
13-1022	Wholesale and Retail Buyers, Except Farm Products
13-1023	Purchasing Agents, Except Wholesale, Retail, and Farm Products
13-1032	Insurance Appraisers, Auto Damage
13-1041	Compliance Officers, Except Agriculture, Construction, Health and Safety, and Transportation
13-1061	Emergency Management Specialists
13-1071	Employment, Recruitment, and Placement Specialists
13-1072	Compensation, Benefits, and Job Analysis Specialists
13-1073	Training and Development Specialists
13-1074	Farm Labor Contractors
13-1078	Human Resources, Training, and Labor Relations Specialists, All Other*
13-1079	Human resources, training, and labor relations specialists, all other
13-1111	Management Analysts
13-1121	Meeting and Convention Planners
13-1141	Compensation, Benefits, and Job Analysis Specialists
13-1161	Market Research Analysts and Marketing Specialists*
13-1199	Business Operations Specialists, All Other*
13-2011	Accountants and Auditors
13-2031	Budget Analysts
13-2041	Credit Analysts
13-2051	Financial Analysts
13-2052	Personal Financial Advisors
13-2053	Insurance Underwriters
13-2061	Financial Examiners

13-2071	Loan Counselors
13-2072	Loan Officers
13-2081	Tax Examiners, Collectors, and Revenue Agents
13-2082	Tax Preparers
13-2099	Financial Specialists, All Other
15-1011	Computer and Information Scientists, Research
15-1021	Computer Programmers
15-1031	Computer Software Engineers, Applications
15-1032	Computer Software Engineers, Systems Software
15-1041	Computer Support Specialists
15-1051	Computer Systems Analysts
15-1061	Database Administrators
15-1071	Network and Computer Systems Administrators
15-1081	Network Systems and Data Communications Analysts
15-1099	Computer specialists, all other
15-1111	Computer and Information Research Scientists
15-1121	Computer Systems Analysts
15-1131	Computer Programmers
15-1132	Software Developers, Applications
15-1133	Software Developers, Systems Software
15-1141	Database Administrators
15-1142	Network and Computer Systems Administrators*
15-1150	Computer Support Specialists
15-1179	Information Security Analysts, Web Developers, and Computer Network Architects
15-1799	Computer Occupations, All Other*
15-2011	Actuaries
15-2021	Mathematicians
15-2031	Operations Research Analysts
15-2041	Statisticians
15-2091	Mathematical Technicians
15-2099	Mathematical Science Occupations, All Other
17-1011	Architects, Except Landscape and Naval
17-1012	Landscape Architects
17-1021	Cartographers and Photogrammetrists
17-1022	Surveyors
17-2011	Aerospace Engineers
17-2021	Agricultural Engineers
17-2031	Biomedical Engineers
17-2041	Chemical Engineers
17-2051	Civil Engineers

17-2061	Computer Hardware Engineers
17-2071	Electrical Engineers
17-2072	Electronics Engineers, Except Computer
17-2081	Environmental Engineers
17-2111	Health and Safety Engineers, Except Mining Safety Engineers and Inspectors
17-2112	Industrial Engineers
17-2121	Marine Engineers and Naval Architects
17-2131	Materials Engineers
17-2141	Mechanical Engineers
17-2151	Mining and Geological Engineers, Including Mining Safety Engineers
17-2161	Nuclear Engineers
17-2171	Petroleum Engineers
17-2199	Engineers, All Other
17-3011	Architectural and Civil Drafters
17-3012	Electrical and Electronics Drafters
17-3013	Mechanical Drafters
17-3019	Drafters, All Other
17-3021	Aerospace Engineering and Operations Technicians
17-3022	Civil Engineering Technicians
17-3023	Electrical and Electronic Engineering Technicians
17-3024	Electro-Mechanical Technicians
17-3025	Environmental Engineering Technicians
17-3026	Industrial Engineering Technicians
17-3027	Mechanical Engineering Technicians
17-3029	Engineering Technicians, Except Drafters, All Other
17-3031	Surveying and Mapping Technicians
19-1010	Agricultural and Food Scientists
19-1011	Animal Scientists
19-1012	Food Scientists and Technologists
19-1013	Soil and Plant Scientists
19-1021	Biochemists and Biophysicists
19-1022	Microbiologists
19-1023	Zoologists and Wildlife Biologists
19-1029	Biological Scientists, All Other
19-1031	Conservation Scientists
19-1032	Foresters
19-1041	Epidemiologists
19-1042	Medical Scientists, Except Epidemiologists
19-1099	Life Scientists, All Other
19-2011	Astronomers

19-2012	Physicists
19-2021	Atmospheric and Space Scientists
19-2031	Chemists
19-2032	Materials Scientists
19-2041	Environmental Scientists and Specialists, Including Health
19-2042	Geoscientists, Except Hydrologists and Geographers
19-2043	Hydrologists
19-2099	Physical Scientists, All Other
19-3011	Economists
19-3021	Market Research Analysts
19-3022	Survey Researchers
19-3031	Clinical, Counseling, and School Psychologists
19-3039	Psychologists, All Other
19-3041	Sociologists
19-3051	Urban and Regional Planners
19-3091	Anthropologists and Archeologists
19-3092	Geographers
19-3093	Historians
19-3094	Political Scientists
19-3099	Social Scientists and Related Workers, All Other
19-4011	Agricultural and Food Science Technicians
19-4021	Biological Technicians
19-4031	Chemical Technicians
19-4041	Geological and Petroleum Technicians
19-4051	Nuclear Technicians
19-4061	Social Science Research Assistants
19-4091	Environmental Science and Protection Technicians, Including Health
19-4092	Forensic Science Technicians
19-4093	Forest and Conservation Technicians
19-4099	Life, Physical, and Social Science Technicians, All Other
21-1021	Child, Family, and School Social Workers
21-1023	Mental Health and Substance Abuse Social Workers
21-1029	Social Workers, All Other
21-1092	Probation Officers and Correctional Treatment Specialists
21-1093	Social and Human Service Assistants
21-1099	Community and social service specialists, all other
21-1798	Community and Social Service Specialists, All Other*
21-2011	Clergy
21-2021	Directors, Religious Activities and Education
21-2099	Religious Workers, All Other

23-1021	Administrative Law Judges, Adjudicators, and Hearing Officers
23-2011	Paralegals and Legal Assistants
25-1011	Business Teachers, Postsecondary
25-1021	Computer Science Teachers, Postsecondary
25-1022	Mathematical Science Teachers, Postsecondary
25-1031	Architecture Teachers, Postsecondary
25-1032	Engineering Teachers, Postsecondary
25-1041	Agricultural Sciences Teachers, Postsecondary
25-1042	Biological Science Teachers, Postsecondary
25-1043	Forestry and Conservation Science Teachers, Postsecondary
25-1051	Atmospheric, Earth, Marine, and Space Sciences Teachers, Postsecondary
25-1052	Chemistry Teachers, Postsecondary
25-1053	Environmental Science Teachers, Postsecondary
25-1054	Physics Teachers, Postsecondary
25-1061	Anthropology and Archeology Teachers, Postsecondary
25-1062	Area, Ethnic, and Cultural Studies Teachers, Postsecondary
25-1063	Economics Teachers, Postsecondary
25-1064	Geography Teachers, Postsecondary
25-1065	Political Science Teachers, Postsecondary
25-1066	Psychology Teachers, Postsecondary
25-1067	Sociology Teachers, Postsecondary
25-1069	Social Sciences Teachers, Postsecondary, All Other
25-1071	Health Specialties Teachers, Postsecondary
25-1072	Nursing Instructors and Teachers, Postsecondary
25-1081	Education Teachers, Postsecondary
25-1082	Library Science Teachers, Postsecondary
25-1111	Criminal Justice and Law Enforcement Teachers, Postsecondary
25-1112	Law Teachers, Postsecondary
25-1113	Social Work Teachers, Postsecondary
25-1121	Art, Drama, and Music Teachers, Postsecondary
25-1122	Communications Teachers, Postsecondary
25-1123	English Language and Literature Teachers, Postsecondary
25-1124	Foreign Language and Literature Teachers, Postsecondary
25-1125	History Teachers, Postsecondary
25-1126	Philosophy and Religion Teachers, Postsecondary
25-1192	Home Economics Teachers, Postsecondary
25-1193	Recreation and Fitness Studies Teachers, Postsecondary
25-1194	Vocational Education Teachers, Postsecondary
25-1199	Postsecondary Teachers, All Other
25-2031	Secondary School Teachers, Except Special and Vocational Education

25-2032	Vocational Education Teachers, Secondary School
25-2043	Special Education Teachers, Secondary School
25-2054	Special Education Teachers, Secondary School
25-4010	Archivists, Curators, and Museum Technicians
25-4011	Archivists
25-4012	Curators
25-4013	Museum Technicians and Conservators
25-4021	Librarians
25-9011	Audio-Visual Collections Specialists
25-9021	Farm and Home Management Advisors
25-9099	Education, Training, and Library Workers, All Other
27-1011	Art Directors
27-1012	Craft Artists
27-1013	Fine Artists, Including Painters, Sculptors, and Illustrators
27-1014	Multi-Media Artists and Animators
27-1021	Commercial and Industrial Designers
27-1022	Fashion Designers
27-1023	Floral Designers
27-1024	Graphic Designers
27-1025	Interior Designers
27-1027	Set and Exhibit Designers
27-1029	Designers, All Other
27-2012	Producers and Directors
27-2021	Athletes and Sports Competitors
27-2031	Dancers
27-2032	Choreographers
27-2041	Music Directors and Composers
27-2042	Musicians and Singers
27-2099	Entertainers and Performers, Sports and Related Workers, All Other
27-3020	News Analysts, Reporters and Correspondents
27-3021	Broadcast News Analysts
27-3041	Editors
27-3042	Technical Writers
27-3043	Writers and Authors
27-4011	Audio and Video Equipment Technicians
27-4012	Broadcast Technicians
27-4013	Radio Operators
27-4014	Sound Engineering Technicians
27-4021	Photographers
27-4031	Camera Operators, Television, Video, and Motion Picture

27-4032	Film and Video Editors
27-4099	Media and Communication Equipment Workers, All Other
29-1011	Chiropractors
29-1020	Dentists
29-1021	Dentists, General
29-1022	Oral and Maxillofacial Surgeons
29-1023	Orthodontists
29-1024	Prosthodontists
29-1029	Dentists, All Other Specialists
29-1031	Dietitians and Nutritionists
29-1041	Optometrists
29-1051	Pharmacists
29-1061	Anesthesiologists
29-1062	Family and General Practitioners
29-1063	Internists, General
29-1064	Obstetricians and Gynecologists
29-1065	Pediatricians, General
29-1066	Psychiatrists
29-1067	Surgeons
29-1069	Physicians and Surgeons, All Other
29-1071	Physician Assistants
29-1081	Podiatrists
29-1111	Registered Nurses
29-1121	Audiologists
29-1122	Occupational Therapists
29-1123	Physical Therapists
29-1124	Radiation Therapists
29-1125	Recreational Therapists
29-1126	Respiratory Therapists
29-1127	Speech-Language Pathologists
29-1128	Therapists, All Other*
29-1129	Therapists, all other
29-1131	Veterinarians
29-1181	Audiologists
29-1199	Health Diagnosing and Treating Practitioners, All Other
29-2011	Medical and Clinical Laboratory Technologists
29-2012	Medical and Clinical Laboratory Technicians
29-2021	Dental Hygienists
29-2031	Cardiovascular Technologists and Technicians
29-2032	Diagnostic Medical Sonographers

29-2033	Nuclear Medicine Technologists
29-2034	Radiologic Technologists and Technicians
29-2037	Radiologic Technologists and Technicians*
29-2041	Emergency Medical Technicians and Paramedics
29-2051	Dietetic Technicians
29-2052	Pharmacy Technicians
29-2053	Psychiatric Technicians
29-2054	Respiratory Therapy Technicians
29-2055	Surgical Technologists
29-2056	Veterinary Technologists and Technicians
29-2061	Licensed Practical and Licensed Vocational Nurses
29-2071	Medical Records and Health Information Technicians
29-2091	Orthotists and Prosthetists
29-2099	Health technologists and technicians, all other
29-2799	Health Technologists and Technicians, All Other*
29-9010	Occupational Health and Safety Specialists and Technicians
29-9011	Occupational Health and Safety Specialists
29-9012	Occupational Health and Safety Technicians
29-9099	Healthcare practitioners and technical workers, all other
29-9799	Healthcare Practitioners and Technical Workers, All Other*
51-8021	Stationary Engineers and Boiler Operators
51-9081	Dental Laboratory Technicians
51-9082	Medical Appliance Technicians
53-1011	Aircraft Cargo Handling Supervisors
53-2011	Airline Pilots, Copilots, and Flight Engineers
53-2012	Commercial Pilots
53-2021	Air Traffic Controllers
53-2022	Airfield Operations Specialists
53-4011	Locomotive Engineers
53-4013	Rail Yard Engineers, Dinkey Operators, and Hostlers
53-5021	Captains, Mates, and Pilots of Water Vessels

Medium Skill Occupations

soc_code	occ_title
11-3071	Transportation, Storage, and Distribution Managers
13-2021	Appraisers and Assessors of Real Estate
23-1012	Judicial Law Clerks
25-4031	Library Technicians
25-9041	Teacher Assistants
27-1026	Merchandise Displayers and Window Trimmers
41-1011	First-Line Supervisors/Managers of Retail Sales Workers
41-1012	First-Line Supervisors/Managers of Non-Retail Sales Workers
41-2011	Cashiers
41-2012	Gaming Change Persons and Booth Cashiers
41-2021	Counter and Rental Clerks
41-2022	Parts Salespersons
41-2031	Retail Salespersons
41-3011	Advertising Sales Agents
41-3021	Insurance Sales Agents
41-3031	Securities, Commodities, and Financial Services Sales Agents
41-3041	Travel Agents
41-3099	Sales Representatives, Services, All Other
41-4011	Sales Representatives, Wholesale and Manufacturing, Technical and Scientific Products
41-4012	Sales Representatives, Wholesale and Manufacturing, Except Technical and Scientific Products
41-9011	Demonstrators and Product Promoters
41-9012	Models
41-9021	Real Estate Brokers
41-9022	Real Estate Sales Agents
41-9031	Sales Engineers
41-9041	Telemarketers
41-9091	Door-To-Door Sales Workers, News and Street Vendors, and Related Workers
41-9099	Sales and related workers, all other
41-9799	Sales and Related Workers, All Other*
43-1011	First-Line Supervisors/Managers of Office and Administrative Support Workers
43-2011	Switchboard Operators, Including Answering Service
43-2021	Telephone Operators
43-2099	Communications Equipment Operators, All Other
43-3011	Bill and Account Collectors
43-3021	Billing and Posting Clerks and Machine Operators
43-3031	Bookkeeping, Accounting, and Auditing Clerks

43-3041	Gaming Cage Workers
43-3051	Payroll and Timekeeping Clerks
43-3061	Procurement Clerks
43-3071	Tellers
43-4011	Brokerage Clerks
43-4021	Correspondence Clerks
43-4031	Court, Municipal, and License Clerks
43-4041	Credit Authorizers, Checkers, and Clerks
43-4051	Customer Service Representatives
43-4061	Eligibility Interviewers, Government Programs
43-4071	File Clerks
43-4081	Hotel, Motel, and Resort Desk Clerks
43-4111	Interviewers, Except Eligibility and Loan
43-4121	Library Assistants, Clerical
43-4131	Loan Interviewers and Clerks
43-4141	New Accounts Clerks
43-4151	Order Clerks
43-4161	Human Resources Assistants, Except Payroll and Timekeeping
43-4171	Receptionists and Information Clerks
43-4181	Reservation and Transportation Ticket Agents and Travel Clerks
43-4199	Information and Record Clerks, All Other
43-5011	Cargo and Freight Agents
43-5021	Couriers and Messengers
43-5031	Police, Fire, and Ambulance Dispatchers
43-5032	Dispatchers, Except Police, Fire, and Ambulance
43-5041	Meter Readers, Utilities
43-5051	Postal Service Clerks
43-5052	Postal Service Mail Carriers
43-5053	Postal Service Mail Sorters, Processors, and Processing Machine Operators
43-5061	Production, Planning, and Expediting Clerks
43-5071	Shipping, Receiving, and Traffic Clerks
43-5081	Stock Clerks and Order Fillers
43-5111	Weighers, Measurers, Checkers, and Samplers, Recordkeeping
43-6011	Executive Secretaries and Administrative Assistants
43-6012	Legal Secretaries
43-6013	Medical Secretaries
43-6014	Secretaries, Except Legal, Medical, and Executive
43-9011	Computer Operators
43-9021	Data Entry Keyers
43-9022	Word Processors and Typists

43-9031	Desktop Publishers
43-9041	Insurance Claims and Policy Processing Clerks
43-9051	Mail Clerks and Mail Machine Operators, Except Postal Service
43-9061	Office Clerks, General
43-9071	Office Machine Operators, Except Computer
43-9081	Proofreaders and Copy Markers
43-9111	Statistical Assistants
43-9199	Office and administrative support workers, all other
43-9799	Office and Administrative Support Workers, All Other*

Low skill occupations

SOC code	Occupation title
11-9012	Farmers and ranchers
29-2081	Opticians, Dispensing
45-1012	Farm Labor Contractors
45-2011	Agricultural Inspectors
45-2021	Animal Breeders
45-2041	Graders and Sorters, Agricultural Products
45-2091	Agricultural Equipment Operators
45-2092	Farmworkers and Laborers, Crop, Nursery, and Greenhouse
45-2093	Farmworkers, Farm and Ranch Animals
45-2099	Agricultural Workers, All Other
45-3011	Fishers and Related Fishing Workers
45-4011	Forest and Conservation Workers
45-4021	Fallers
45-4022	Logging Equipment Operators
45-4023	Log Graders and Scalers
45-4029	Logging Workers, All Other
47-1011	First-Line Supervisors/Managers of Construction Trades and Extraction Workers
47-2011	Boilermakers
47-2021	Brickmasons and Blockmasons
47-2022	Stonemasons
47-2031	Carpenters
47-2041	Carpet Installers
47-2042	Floor Layers, Except Carpet, Wood, and Hard Tiles
47-2043	Floor Sanders and Finishers
47-2044	Tile and Marble Setters
47-2051	Cement Masons and Concrete Finishers
47-2053	Terrazzo Workers and Finishers
47-2061	Construction Laborers
47-2071	Paving, Surfacing, and Tamping Equipment Operators
47-2072	Pile-Driver Operators
47-2073	Operating Engineers and Other Construction Equipment Operators
47-2081	Drywall and Ceiling Tile Installers
47-2082	Tapers
47-2111	Electricians
47-2121	Glaziers

47-2130	Insulation Workers
47-2131	Insulation Workers, Floor, Ceiling, and Wall
47-2132	Insulation Workers, Mechanical
47-2141	Painters, Construction and Maintenance
47-2142	Paperhangers
47-2151	Pipelayers
47-2152	Plumbers, Pipefitters, and Steamfitters
47-2161	Plasterers and Stucco Masons
47-2171	Reinforcing Iron and Rebar Workers
47-2181	Roofers
47-2211	Sheet Metal Workers
47-2221	Structural Iron and Steel Workers
47-3011	Helpers--Brickmasons, Blockmasons, Stonemasons, and Tile and Marble Setters
47-3012	Helpers--Carpenters
47-3013	Helpers--Electricians
47-3014	Helpers--Painters, Paperhangers, Plasterers, and Stucco Masons
47-3015	Helpers--Pipelayers, Plumbers, Pipefitters, and Steamfitters
47-3016	Helpers--Roofers
47-3019	Helpers, Construction Trades, All Other
47-4011	Construction and Building Inspectors
47-4021	Elevator Installers and Repairers
47-4031	Fence Erectors
47-4041	Hazardous Materials Removal Workers
47-4051	Highway Maintenance Workers
47-4061	Rail-Track Laying and Maintenance Equipment Operators
47-4071	Septic Tank Servicers and Sewer Pipe Cleaners
47-4091	Segmental Pavers
47-4099	Construction and related workers, all other
47-4799	Construction and Related Workers, All Other*
47-5011	Derrick Operators, Oil and Gas
47-5012	Rotary Drill Operators, Oil and Gas
47-5013	Service Unit Operators, Oil, Gas, and Mining
47-5021	Earth Drillers, Except Oil and Gas
47-5031	Explosives Workers, Ordnance Handling Experts, and Blasters
47-5041	Continuous Mining Machine Operators
47-5042	Mine Cutting and Channeling Machine Operators
47-5049	Mining Machine Operators, All Other
47-5051	Rock Splitters, Quarry
47-5061	Roof Bolters, Mining
47-5071	Roustabouts, Oil and Gas

47-5081	Helpers--Extraction Workers
47-5099	Extraction Workers, All Other
49-1011	First-Line Supervisors/Managers of Mechanics, Installers, and Repairers
49-2011	Computer, Automated Teller, and Office Machine Repairers
49-2021	Radio Mechanics
49-2022	Telecommunications Equipment Installers and Repairers, Except Line Installers
49-2091	Avionics Technicians
49-2092	Electric Motor, Power Tool, and Related Repairers
49-2093	Electrical and Electronics Installers and Repairers, Transportation Equipment
49-2094	Electrical and Electronics Repairers, Commercial and Industrial Equipment
49-2095	Electrical and Electronics Repairers, Powerhouse, Substation, and Relay
49-2096	Electronic Equipment Installers and Repairers, Motor Vehicles
49-2097	Electronic Home Entertainment Equipment Installers and Repairers
49-2098	Security and Fire Alarm Systems Installers
49-3011	Aircraft Mechanics and Service Technicians
49-3021	Automotive Body and Related Repairers
49-3022	Automotive Glass Installers and Repairers
49-3023	Automotive Service Technicians and Mechanics
49-3031	Bus and Truck Mechanics and Diesel Engine Specialists
49-3041	Farm Equipment Mechanics
49-3042	Mobile Heavy Equipment Mechanics, Except Engines
49-3043	Rail Car Repairers
49-3051	Motorboat Mechanics
49-3052	Motorcycle Mechanics
49-3053	Outdoor Power Equipment and Other Small Engine Mechanics
49-3091	Bicycle Repairers
49-3092	Recreational Vehicle Service Technicians
49-3093	Tire Repairers and Changers
49-9011	Mechanical Door Repairers
49-9012	Control and Valve Installers and Repairers, Except Mechanical Door
49-9021	Heating, Air Conditioning, and Refrigeration Mechanics and Installers
49-9031	Home Appliance Repairers
49-9041	Industrial Machinery Mechanics
49-9042	Maintenance and Repair Workers, General
49-9043	Maintenance Workers, Machinery
49-9044	Millwrights
49-9045	Refractory Materials Repairers, Except Brickmasons
49-9051	Electrical Power-Line Installers and Repairers
49-9052	Telecommunications Line Installers and Repairers
49-9061	Camera and Photographic Equipment Repairers

49-9062	Medical Equipment Repairers
49-9063	Musical Instrument Repairers and Tuners
49-9064	Watch Repairers
49-9069	Precision Instrument and Equipment Repairers, All Other
49-9071	Maintenance and Repair Workers, General
49-9091	Coin, Vending, and Amusement Machine Servicers and Repairers
49-9092	Commercial Divers
49-9093	Fabric Menders, Except Garment
49-9094	Locksmiths and Safe Repairers
49-9095	Manufactured Building and Mobile Home Installers
49-9096	Riggers
49-9097	Signal and Track Switch Repairers
49-9098	Helpers--Installation, Maintenance, and Repair Workers
49-9099	Installation, maintenance, and repair workers, all other
49-9799	Installation, Maintenance, and Repair Workers, All Other*
51-2011	Aircraft Structure, Surfaces, Rigging, and Systems Assemblers
51-2021	Coil Winders, Tapers, and Finishers
51-2022	Electrical and Electronic Equipment Assemblers
51-2023	Electromechanical Equipment Assemblers
51-2031	Engine and Other Machine Assemblers
51-2041	Structural Metal Fabricators and Fitters
51-2091	Fiberglass Laminators and Fabricators
51-2092	Team Assemblers
51-2093	Timing Device Assemblers, Adjusters, and Calibrators
51-2099	Assemblers and Fabricators, All Other
51-3011	Bakers
51-3021	Butchers and Meat Cutters
51-3022	Meat, Poultry, and Fish Cutters and Trimmers
51-3023	Slaughterers and Meat Packers
51-3091	Food and Tobacco Roasting, Baking, and Drying Machine Operators and Tenders
51-3092	Food Batchmakers
51-3093	Food Cooking Machine Operators and Tenders
51-4011	Computer-Controlled Machine Tool Operators, Metal and Plastic
51-4012	Numerical Tool and Process Control Programmers
51-4021	Extruding and Drawing Machine Setters, Operators, and Tenders, Metal and Plastic
51-4022	Forging Machine Setters, Operators, and Tenders, Metal and Plastic
51-4023	Rolling Machine Setters, Operators, and Tenders, Metal and Plastic
51-4031	Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic
51-4032	Drilling and Boring Machine Tool Setters, Operators, and Tenders, Metal and Plastic
51-4033	Grinding, Lapping, Polishing, and Buffing Machine Tool Setters, Operators, and Tenders, Metal

	and Plastic
51-4034	Lathe and Turning Machine Tool Setters, Operators, and Tenders, Metal and Plastic
51-4035	Milling and Planing Machine Setters, Operators, and Tenders, Metal and Plastic
51-4041	Machinists
51-4051	Metal-Refining Furnace Operators and Tenders
51-4052	Pourers and Casters, Metal
51-4061	Model Makers, Metal and Plastic
51-4062	Patternmakers, Metal and Plastic
51-4071	Foundry Mold and Coremakers
51-4072	Molding, Coremaking, and Casting Machine Setters, Operators, and Tenders, Metal and Plastic
51-4081	Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic
51-4111	Tool and Die Makers
51-4121	Welders, Cutters, Solderers, and Brazers
51-4122	Welding, Soldering, and Brazing Machine Setters, Operators, and Tenders
51-4191	Heat Treating Equipment Setters, Operators, and Tenders, Metal and Plastic
51-4192	Lay-Out Workers, Metal and Plastic
51-4193	Plating and Coating Machine Setters, Operators, and Tenders, Metal and Plastic
51-4194	Tool Grinders, Filers, and Sharpeners
51-4199	Metal Workers and Plastic Workers, All Other
51-5011	Bindery Workers
51-5012	Bookbinders
51-5021	Job Printers
51-5022	Prepress Technicians and Workers
51-5023	Printing Machine Operators
51-5111	Prepress Technicians and Workers
51-5112	Printing Press Operators
51-5113	Print Binding and Finishing Workers
51-6011	Laundry and Dry-Cleaning Workers
51-6021	Pressers, Textile, Garment, and Related Materials
51-6031	Sewing Machine Operators
51-6041	Shoe and Leather Workers and Repairers
51-6042	Shoe Machine Operators and Tenders
51-6051	Sewers, Hand
51-6052	Tailors, Dressmakers, and Custom Sewers
51-6061	Textile Bleaching and Dyeing Machine Operators and Tenders
51-6062	Textile Cutting Machine Setters, Operators, and Tenders
51-6063	Textile Knitting and Weaving Machine Setters, Operators, and Tenders
51-6064	Textile Winding, Twisting, and Drawing Out Machine Setters, Operators, and Tenders
51-6091	Extruding and Forming Machine Setters, Operators, and Tenders, Synthetic and Glass Fibers
51-6092	Fabric and Apparel Patternmakers

51-6093	Upholsterers
51-6099	Textile, Apparel, and Furnishings Workers, All Other
51-7011	Cabinetmakers and Bench Carpenters
51-7021	Furniture Finishers
51-7031	Model Makers, Wood
51-7032	Patternmakers, Wood
51-7041	Sawing Machine Setters, Operators, and Tenders, Wood
51-7042	Woodworking Machine Setters, Operators, and Tenders, Except Sawing
51-7099	Woodworkers, All Other
51-8011	Nuclear Power Reactor Operators
51-8012	Power Distributors and Dispatchers
51-8013	Power Plant Operators
51-8031	Water and Liquid Waste Treatment Plant and System Operators
51-8091	Chemical Plant and System Operators
51-8092	Gas Plant Operators
51-8093	Petroleum Pump System Operators, Refinery Operators, and Gaugers
51-8099	Plant and System Operators, All Other
51-9011	Chemical Equipment Operators and Tenders
51-9012	Separating, Filtering, Clarifying, Precipitating, and Still Machine Setters, Operators, and Tenders
51-9021	Crushing, Grinding, and Polishing Machine Setters, Operators, and Tenders
51-9022	Grinding and Polishing Workers, Hand
51-9023	Mixing and Blending Machine Setters, Operators, and Tenders
51-9031	Cutters and Trimmers, Hand
51-9032	Cutting and Slicing Machine Setters, Operators, and Tenders
51-9041	Extruding, Forming, Pressing, and Compacting Machine Setters, Operators, and Tenders
51-9051	Furnace, Kiln, Oven, Drier, and Kettle Operators and Tenders
51-9061	Inspectors, Testers, Sorters, Samplers, and Weighers
51-9071	Jewelers and Precious Stone and Metal Workers
51-9083	Ophthalmic Laboratory Technicians
51-9111	Packaging and Filling Machine Operators and Tenders
51-9121	Coating, Painting, and Spraying Machine Setters, Operators, and Tenders
51-9122	Painters, Transportation Equipment
51-9123	Painting, Coating, and Decorating Workers
51-9131	Photographic Process Workers
51-9132	Photographic Processing Machine Operators
51-9141	Semiconductor Processors
51-9151	Photographic Process Workers and Processing Machine Operators
51-9191	Cementing and Gluing Machine Operators and Tenders
51-9192	Cleaning, Washing, and Metal Pickling Equipment Operators and Tenders
51-9193	Cooling and Freezing Equipment Operators and Tenders

51-9194	Etchers and Engravers
51-9195	Molders, Shapers, and Casters, Except Metal and Plastic
51-9196	Paper Goods Machine Setters, Operators, and Tenders
51-9197	Tire Builders
51-9198	Helpers--Production Workers
51-9199	Production workers, all other
51-9399	Production Workers, All Other*
53-3011	Ambulance Drivers and Attendants, Except Emergency Medical Technicians
53-3041	Taxi Drivers and Chauffeurs
53-3099	Motor Vehicle Operators, All Other
53-4021	Railroad Brake, Signal, and Switch Operators
53-4031	Railroad Conductors and Yardmasters
53-4041	Subway and Streetcar Operators
53-4099	Rail Transportation Workers, All Other
53-5011	Sailors and Marine Oilers
53-5022	Motorboat Operators
53-5031	Ship Engineers
53-6011	Bridge and Lock Tenders
53-6021	Parking Lot Attendants
53-6031	Service Station Attendants
53-6041	Traffic Technicians
53-6099	Transportation Workers, All Other
53-7011	Conveyor Operators and Tenders
53-7021	Crane and Tower Operators
53-7031	Dredge Operators
53-7032	Excavating and Loading Machine and Dragline Operators
53-7033	Loading Machine Operators, Underground Mining
53-7041	Hoist and Winch Operators
53-7051	Industrial Truck and Tractor Operators
53-7061	Cleaners of Vehicles and Equipment
53-7062	Laborers and Freight, Stock, and Material Movers, Hand
53-7063	Machine Feeders and Offbearers
53-7064	Packers and Packagers, Hand
53-7071	Gas Compressor and Gas Pumping Station Operators
53-7072	Pump Operators, Except Wellhead Pumpers
53-7073	Wellhead Pumpers
53-7081	Refuse and Recyclable Material Collectors
53-7111	Shuttle Car Operators
53-7121	Tank Car, Truck, and Ship Loaders
53-7199	Material Moving Workers, All Other

31-1011	Home Health Aides
31-1012	Nursing Aides, Orderlies, and Attendants
31-1013	Psychiatric Aides
31-2011	Occupational Therapist Assistants
31-2012	Occupational Therapist Aides
31-2021	Physical Therapist Assistants
31-2022	Physical Therapist Aides
31-9011	Massage Therapists
31-9091	Dental Assistants
31-9092	Medical Assistants
31-9093	Medical Equipment Preparers
31-9094	Medical Transcriptionists
31-9095	Pharmacy Aides
31-9096	Veterinary Assistants and Laboratory Animal Caretakers
31-9099	Healthcare support workers, all other
31-9799	Healthcare Support Workers, All Other*
33-1011	First-Line Supervisors/Managers of Correctional Officers
33-1012	First-Line Supervisors/Managers of Police and Detectives
33-1021	First-Line Supervisors/Managers of Fire Fighting and Prevention Workers
33-1099	First-Line Supervisors of Protective Service Workers, All Other
33-2011	Fire Fighters
33-2021	Fire Inspectors and Investigators
33-2022	Forest Fire Inspectors and Prevention Specialists
33-3011	Bailiffs
33-3012	Correctional Officers and Jailers
33-3021	Detectives and Criminal Investigators
33-3031	Fish and Game Wardens
33-3041	Parking Enforcement Workers
33-3051	Police and Sheriff's Patrol Officers
33-3052	Transit and Railroad Police
33-9011	Animal Control Workers
33-9021	Private Detectives and Investigators
33-9031	Gaming Surveillance Officers and Gaming Investigators
33-9032	Security Guards
33-9091	Crossing Guards
33-9092	Lifeguards, Ski Patrol, and Other Recreational Protective Service Workers
33-9093	Transportation Security Screeners* (federal only)
33-9099	Protective Service Workers, All Other *
35-1011	Chefs and Head Cooks
35-1012	First-Line Supervisors/Managers of Food Preparation and Serving Workers

35-2011	Cooks, Fast Food
35-2012	Cooks, Institution and Cafeteria
35-2013	Cooks, Private Household
35-2014	Cooks, Restaurant
35-2015	Cooks, Short Order
35-2019	Cooks, All Other
35-2021	Food Preparation Workers
35-3011	Bartenders
35-3021	Combined Food Preparation and Serving Workers, Including Fast Food
35-3022	Counter Attendants, Cafeteria, Food Concession, and Coffee Shop
35-3031	Waiters and Waitresses
35-3041	Food Servers, Nonrestaurant
35-9011	Dining Room and Cafeteria Attendants and Bartender Helpers
35-9021	Dishwashers
35-9031	Hosts and Hostesses, Restaurant, Lounge, and Coffee Shop
35-9099	Food Preparation and Serving Related Workers, All Other
37-1011	First-Line Supervisors/Managers of Housekeeping and Janitorial Workers
37-1012	First-Line Supervisors/Managers of Landscaping, Lawn Service, and Groundskeeping Workers
37-2011	Janitors and Cleaners, Except Maids and Housekeeping Cleaners
37-2012	Maids and Housekeeping Cleaners
37-2019	Building Cleaning Workers, All Other
37-2021	Pest Control Workers
37-3011	Landscaping and Groundskeeping Workers
37-3012	Pesticide Handlers, Sprayers, and Applicators, Vegetation
37-3013	Tree Trimmers and Pruners
37-3019	Grounds Maintenance Workers, All Other
39-1011	Gaming Supervisors
39-1012	Slot Key Persons
39-1021	First-Line Supervisors/Managers of Personal Service Workers
39-2011	Animal Trainers
39-2021	Nonfarm Animal Caretakers
39-3011	Gaming Dealers
39-3012	Gaming and Sports Book Writers and Runners
39-3019	Gaming Service Workers, All Other
39-3021	Motion Picture Projectionists
39-3031	Ushers, Lobby Attendants, and Ticket Takers
39-3091	Amusement and Recreation Attendants
39-3092	Costume Attendants
39-3093	Locker Room, Coatroom, and Dressing Room Attendants
39-3099	Entertainment Attendants and Related Workers, All Other

39-4011	Embalmers
39-4021	Funeral Attendants
39-4831	Funeral Service Managers, Directors, Morticians, and Undertakers
39-5011	Barbers
39-5012	Hairdressers, Hairstylists, and Cosmetologists
39-5091	Makeup Artists, Theatrical and Performance
39-5092	Manicurists and Pedicurists
39-5093	Shampooers
39-5094	Skin Care Specialists
39-6011	Baggage Porters and Bellhops
39-6012	Concierges
39-6021	Tour Guides and Escorts
39-6022	Travel Guides
39-6031	Flight Attendants
39-6032	Transportation Attendants, Except Flight Attendants and Baggage Porters
39-7011	Tour Guides and Escorts
39-7012	Travel Guides
39-9011	Child Care Workers
39-9021	Personal and Home Care Aides
39-9031	Fitness Trainers and Aerobics Instructors
39-9032	Recreation Workers
39-9041	Residential Advisors
39-9099	Personal Care and Service Workers, All Other
53-2031	Flight Attendants
53-3021	Bus Drivers, Transit and Intercity
53-3022	Bus Drivers, School
53-3031	Driver/Sales Workers
53-3032	Truck Drivers, Heavy and Tractor-Trailer
53-3033	Truck Drivers, Light Or Delivery Services
53-4012	Locomotive Firers
53-6051	Transportation Inspectors
53-6061	Transportation Attendants, Except Flight Attendants

Table B3: Classification of NAICS2007 4-digit industry codes in different technological groups (high-tech, medium-tech and low-tech)

NAICS2007 4-digit industry codes	***Description***
High-Tech Industries	
3254	Pharmaceutical and Medicine Manufacturing
3332	Industrial Machinery Manufacturing
3333	Commercial and Service Industry Machinery Manufacturing
3336	Engine, Turbine, and Power Transmission Equipment Manufacturing
3339	Other General Purpose Machinery Manufacturing
3341	Computer and Peripheral Equipment Manufacturing
3342	Communications Equipment Manufacturing
3344	Semiconductor and Other Electronic Component Manufacturing
3353	Electrical Equipment Manufacturing
3364	Aerospace Product and Parts Manufacturing
3366	Ship and Boat Building
3391	Medical Equipment and Supplies Manufacturing
Med-Tech Industries	
3346	Manufacturing and Reproducing Magnetic and Optical Media
3335	Metalworking Machinery Manufacturing
3345	Navigational, Measuring, Electromedical, and Control Instruments Manufacturing
3351	Electric Lighting Equipment Manufacturing
3352	Household Appliance Manufacturing
3359	Other Electrical Equipment and Component Manufacturing
3361	Motor Vehicle Manufacturing
3363	Motor Vehicle Parts Manufacturing
3365	Railroad Rolling Stock Manufacturing
3369	Other Transportation Equipment Manufacturing
3399	Other Miscellaneous Manufacturing
Low-Tech Industries	
3111	Animal Food Manufacturing
3112	Grain and Oilseed Milling
3113	Sugar and Confectionery Product Manufacturing
3114	Fruit and Vegetable Preserving and Specialty Food Manufacturing
3115	Dairy Product Manufacturing
3116	Animal Slaughtering and Processing
3117	Seafood Product Preparation and Packaging
3118	Bakeries and Tortilla Manufacturing

3119	Other Food Manufacturing
3121	Beverage Manufacturing
3122	Tobacco Manufacturing
3131	Fiber, Yarn, and Thread Mills
3132	Fabric Mills
3133	Textile and Fabric Finishing and Fabric Coating Mills
3141	Textile Furnishings Mills
3149	Other Textile Product Mills
3151	Apparel Knitting Mills
3152	Cut and Sew Apparel Manufacturing
3159	Apparel Accessories and Other Apparel Manufacturing
3161	Leather and Hide Tanning and Finishing
3162	Footwear Manufacturing
3169	Other Leather and Allied Product Manufacturing
3211	Sawmills and Wood Preservation
3212	Veneer, Plywood, and Engineered Wood Product Manufacturing
3219	Other Wood Product Manufacturing
3221	Pulp, Paper, and Paperboard Mills
3222	Converted Paper Product Manufacturing
3241	Petroleum and Coal Products Manufacturing
3251	Basic Chemical Manufacturing
3252	Resin, Synthetic Rubber, and Artificial Synthetic Fibers and Filaments Manufacturing
3253	Pesticide, Fertilizer, and Other Agricultural Chemical Manufacturing
3255	Paint, Coating, and Adhesive Manufacturing
3256	Soap, Cleaning Compound, and Toilet Preparation Manufacturing
3259	Other Chemical Product and Preparation Manufacturing
3261	Plastics Product Manufacturing
3262	Rubber Product Manufacturing
3271	Clay Product and Refractory Manufacturing
3272	Glass and Glass Product Manufacturing
3273	Cement and Concrete Product Manufacturing
3274	Lime and Gypsum Product Manufacturing
3279	Other Nonmetallic Mineral Product Manufacturing
3311	Iron and Steel Mills and Ferroalloy Manufacturing
3312	Steel Product Manufacturing from Purchased Steel
3313	Alumina and Aluminum Production and Processing
3314	Nonferrous Metal (except Aluminum) Production and Processing
3315	Foundries
3321	Forging and Stamping

3322	Cutlery and Handtool Manufacturing
3323	Architectural and Structural Metals Manufacturing
3324	Boiler, Tank, and Shipping Container Manufacturing
3325	Hardware Manufacturing
3326	Spring and Wire Product Manufacturing
3327	Machine Shops; Turned Product; and Screw, Nut, and Bolt Manufacturing
3328	Coating, Engraving, Heat Treating, and Allied Activities
3329	Other Fabricated Metal Product Manufacturing
3331	Agriculture, Construction, and Mining Machinery Manufacturing
3343	Audio and Video Equipment Manufacturing
3362	Motor Vehicle Body and Trailer Manufacturing
3371	Household and Institutional Furniture and Kitchen Cabinet Manufacturing
3372	Office Furniture (including Fixtures) Manufacturing
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